Essays on Matching in Labor Economics

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A dissertation presented

by

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to

The Committee on Degrees in Business Economics

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

in the subject of

Business Economics

Harvard University

Cambridge, Massachusetts

May 2013

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Abstract

In this dissertation, I present three essays on matching and assignment in labor economics. The first chapter presents an integrated model of occupation choice, spouse choice, family labor supply, and fertility. Two key features of the model are that occupations differ both in wages and in an amenity termed *flexibility*, and that children require a nontrivial amount of parental time that has no market substitute. I show that occupations with more costly flexibility, modeled as a nonlinearity in wages, have a lower fraction of women, less positive assortative mating on earnings, and lower fertility among dual-career couples. Costly flexibility may induce high-earning couples to share home production, which rewards husbands who are simultaneously high-earning and productive in child care. Empirical evidence broadly supports the main theoretical predictions with respect to the tradeoffs between marriage market and career outcomes.

In the second chapter, I use the University of Michigan Law School Alumni Survey to investigate the interaction between assortative mating and the career and family outcomes of high-ability women. Women with higher earnings potential at the time of law school graduation have higher-earning spouses and more children 15 years after graduation. As the earnings penalty from reduced labor supply decreased over the sample, women with higher-earning spouses and more children reported shorter work weeks and were less likely to be in the labor force. Decreasing the career cost of non-work may have the unintended result of reducing the labor supply of the highest-ability women, as their high-earning spouses give them the option to temporarily exit the labor force.

The third chapter addresses specification choice in empirical peer effects models. Predicting the impact of altering classroom composition on student outcomes has proven an unexpected challenge in the experimental literature. I use the experimental data of Duflo et al. (2011) to evaluate the out-of-sample predictive accuracy of popular reduced form peer effects specifications. I find that predictions of the impact of ability tracking on outcomes are highly sensitive to the choice of peer group summary statistics and functional form assumptions. Standard model selection criteria provide some guidance in selecting among peer effects specifications.

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Acknowledgments

Of all the good luck I've had during my six years of graduate school, I have been luckiest in my mentors. They have been role models not only intellectually but personally, constantly inspiring me to be more curious and thoughtful and to conduct myself with focus, integrity, compassion, and generosity.

When asked by my MBA classmates to describe Claudia Goldin, I replied, "Claudia's who I want to be when I grow up." Through years of conversations at the NBER, both while dog-training and not, Claudia has challenged me to see the world as a historian, embracing detail and idiosyncracy rather than abstracting from them and constantly testing theory with empirical precision. Claudia is a great advocate for all graduate students, even those who get lost or stray, and is a model for how a successful woman can mentor and inspire other women.

I first met Al Roth at my BusEc interview, when I betrayed my utter ignorance at anything having to do with matching. Since then, Al's advice has been invaluable through endless field changes, topic changes, failed models, and existential crises. What started as an off-handed topic suggestion in his office during third year not only resulted in a job market paper but provided the motivation to embark on a research career. Al's genuine intellectual curiosity has inspired me to take risks in my research and "be the best weird I can be."

I was very fortunate to meet Chris Avery in labor lunch the spring of my fifth year. It was through our numerous meetings in the fall that my job market paper came together, as Chris showed me how to turn theorems and simulations in to a living, breathing applied theory paper. Chris has also become a good friend and constant source of research ideas, and I look forward to our future collaborations.

Finally, I have learned an incredible amount from Larry Katz, who welcomed me as a fifth year in his labor courses and answered my many strange questions. Larry's encyclopedic knowledge is a never-ending inspiration to work harder and longer to try to put all the puzzle pieces together.

The third chapter of my dissertation benefitted greatly from conversations with Gary Chamberlain, Guido Imbens, Michal Kolesar, and Kelly Shue during my third year.

I would like to thank Jerry Green and Drew Fudenberg, who admitted me to BusEc as a senior in college and have provided advice and encouragement ever since. I am grateful to the economics department graduate coordinators, Nicole Tateosian and Brenda Piquet, who were always there with chocolate, Kleenex, and the right person to call to solve any crisis. I am also grateful to the Harvard Business School doctoral programs office, especially Janice McCormick, Dianne Le, and John Korn.

One of the best parts of graduate school is the friendships I made during my six years. I am thankful for my many meals and discussions with Marcella Alsan, Itai Ashlagi, Catherine Barrera, Thomas Covert, Ian Dew-Becker, Clayton Featherstone, Duncan Gilchrist, John William Hatfield, Nathaniel Hilger, Scott Kominers, Jacob Leshno, Aurelie Ouss, Alex Peysakhovich, Dana Rotz, Emily Glassberg Sands, and Chenzi Xu. The Harvard Business School Class of 2012 Section C provided continued real-world illustrations of my research.

Funding from Harvard Business School Doctoral Programs, a Harvard University Dissertation Completion Fellowship, and the Sandra Ohrn Family Foundation is gratefully acknowledged. Access to the data used in the second chapter was generously provided by Terry Adams, JJ Prescott, and the University of Michigan Law School Alumni Survey data team. Pascaline Dupas graciously provided the data used in the third chapter and answers to many questions.

Finally, I give my love and thanks to Anita Giobbie-Hurder and Piyush Shanker Agram, who stuck with me through the turbulence.

To my mother, Piyush, and Q

Chapter 1

An Integrated Model of Occupation Choice, Spouse Choice, and Family Labor Supply

1.1 Introduction

What does it mean to "have it all"? For both men and women, the canonical list includes a successful career, an egalitarian marriage, and children. These goals are not pursued in isolation: some are achieved in partnership with others, and all are constrained by markets. A large and established literature has investigated the interaction of subsets of these markets, documenting, for example, the interplay between marriage market conditions and educational investment (Angrist, 2002; Chiappori et al., 2009; Lafortune, 2010) and fertility and female labor supply (Angrist and Evans, 1998; Heckman and MaCurdy, 1980; Nakamura and Nakamura, 1994).

In this paper I develop an integrated model of occupation choice, spouse choice, family labor supply, and fertility that unifies a broad empirical literature on career and family and provides predictions on the relationship among occupation choice, marriage market outcomes, and female labor supply. Building on a growing empirical literature on the career cost of family in high-earning, highly-educated professions, I investigate the relationship between occupational characteristics, in particular those related to labor supply, and equilibrium sorting in the marriage market, and show how marriage market dynamics affect the decisions of women to enter high-earning, demanding occupations and their subsequent labor supply and fertility decisions.

The literature on female occupation choice has traditionally assumed that women provide the majority of child-related home production and focused on women's preferences for *flexibility*, or a set of amenities that allow for easier coordination between home production and market work. The seminal work of Mincer and Polachek (1974) first posited that, as secondary earners in the family, women would select into occupations with low human capital depreciation from child-related spells of non-work. Subsequent studies have shown the willingness of mothers to accept lower wages in exchange for shorter hours to accommodate child-rearing responsibilities (Blank, 1989; Altonji and Paxson, 1992; Loprest, 1992; Goldin, 2006). As women have entered high-earning professions, they have disproportionately entered subspecialties such as dermatology and professions such as pharmacy in which flexibility is relatively inexpensive (Goldin and Katz, 2011, 2012).

Recent analyses of time use data, however, show that men, and in particular educated men, are providing an increasing fraction of child-related home production (Guryan et al., 2008; Feyrer et al., 2008; Ramey and Ramey, 2010). Feyrer et al. (2008) argue that this increase stems from greater bargaining power of wives due to higher wages (see Bianchi et al. (2000) on the relationship between wives' wages and husbands' time spent in home production). The division of child-related home production between husbands and wives has become increasingly important as hours in high-paying occupations for men have increased (Kuhn and Lozano, 2008) and parents are simultaneously investing far greater amounts of time in children of all ages (Guryan et al., 2008; Ramey and Ramey, 2010).

For women who enter inflexible occupations, moreover, the choice of spouse and resulting intra-household bargaining can have substantial impacts on the long-term career cost of family. The high cost of flexibility for women in business, and in particular in finance and professional services, is one of the leading explanations for the substantial gender earnings gap and the paucity of women in top positions (Bertrand and Hallock, 2001; Bertrand et al., 2010).[1] Using detailed retrospective data from an elite Masters of Business Administration (MBA) program, Bertrand et al. (2010) find that fifty-seven percent of the gender earnings gap in business can be explained by non-work spells and shorter hours, mostly due to the presence of children. However, MBA mothers with lower-earning or less-educated spouses exhibit significantly greater labor supply than mothers with a high-earning or equally-educated spouse.[2] Detailed individual observables allow Bertrand et al. (2010) to rule out selection as a driver of this result, as MBA mothers are positively selected on school performance.

I construct a two-period rational expectations model of educational investment and the marriage market building on that of Chiappori et al. (2009).[3] In the first period, individuals choose whether to invest in schooling to enter a high-earning occupation in which an occupational amenity, flexibility over labor supply, may be costly. They then make marriage, fertility, and family labor supply decisions. The key frictions in the model stem from the interactions among the cost of flexibility, which I model as a nonlinearity in wages or the opportunity cost of time spent on child-related home production, the demand of children for parental time that has no market substitute, and relative productivity of husbands with respect to wives in providing this parental time.

I first solve for equilibrium occupation choice, marriage market outcomes, fertility, and labor supply when flexibility in the high-earning occupation is costless. When men and women have

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[1] Additional explanations span several disciplines and include women having a distaste for competition (Niederle and Vesterlund, 2007), an unwillingness of women to negotiate on one's own behalf for advancement (Babcock and Laschever, 2003), and gender discrimination (Bertrand et al., 2005).

[2] Bertrand et al. (2010) define "lower-earning" as having labor market income of $200,000 per year or less. Thus, income effects alone are unlikely to explain the labor supply response documented in their work.

[3] Chiappori et al. (2009) propose that women now constitute the majority of college graduates due to labor market and marriage market returns from college that exceed those of men. They introduce the two-period framework that I build on as well as the assumption that children require some amount of home production that has no market substitute. I augment their model by allowing for endogenous fertility and marriage market sorting, as well as introducing occupational amenities.

identical labor market opportunities and women have an advantage in child care production, women always have a lower return to entering the high-earning occupation than men. The mechanism through which this occurs depends on the available home production technology: women in the high-earning occupation either reduce their labor supply in order to care for children; they forgo having children and through marriage market bargaining incur most of the lost utility from children; or they are primary breadwinners but their husbands are less productive in the home than the wives of high-earning men.

I then introduce costly flexibility in the high-earning occupation. When children require non-trivial amounts of parental time, individuals in high-earning occupations with costlier flexibility are less likely to achieve the triad of career, family, and equal-earning spouse. Women are less likely to enter the high-earning occupation, high-earning married couples are less likely to have children, and high-earning individuals are less likely to marry one another. An important corollary of this result is that women in high-earning occupations with costlier flexibility who achieve "career and family" are more likely to be married to lower-earning men or men less educated than themselves. Decreasing the cost of flexibility may simultaneously increase the fraction of women in a high-earning occupation while decreasing their labor supply, as both fertility and positive sorting in the marriage market become more attractive.

When flexibility is costly, an equilibrium exists in which individuals in the high-earning occupation marry one another and share child care. The optimality of this arrangement follows directly from nonlinearities in earnings: it may be less costly for high-earning fathers who are less efficient in the home to provide some child care than for the mother to purchase flexibility and provide all child care. When men vary in child care productivity, the sharing of home production impacts the relationship between home productivity and the incentives of men to enter the high-earning occupation. Costless flexibility discourages men who are productive in the home from entering the high-earning occupation, whereas the sharing of child care rewards husbands who are simultaneously high-earning and productive in child care.

I present time trends from the U.S. Census and American Community Survey that support the predictions of my model in Section 1.8. Variation across professional occupations in women's achievement of career and family, the fertility decisions of dual-career professional couples, and the probability a professional woman with career and family has a less-educated husband is consistent with the predictions of my model and estimates of the cost of flexibility across high-earning professions by others (Goldin and Katz, 2011). The fraction of dual-career professional couples with children and the fraction of professional women achieving "career and family" who have husbands less-educated than themselves have both increased over the past thirty years. This suggests that the tradeoff between positive assortative mating and career and family may become increasingly important in future cohorts.

I build on a robust theoretical literature on marriage market matching. Becker (1973) first posited that equilibrium sorting in a marriage market is a function of the complementarity or substitutability of agents' traits in home production. Adding occupational time flexibility in a framework of marriage, fertility, and investment decisions produces predictions that differ from those stemming from changes in spot wages, which previous work had assumed (Gronau, 1977; Chiappori et al., 2009). In addition, allowing for individual heterogeneity in child-related home productivity results in a rich set of marriage market equilibria and investment decisions that contributes to a growing literature on multi-dimensional matching in marriage markets (Bergstrom and Bagnoli, 1993; Hitsch, Hortacsu and Ariely, 2010; Lee, 2011; Chiappori, Oreffice and Quintana-Domeque, 2010).

The paper proceeds as follows. Section 1.2 provides an illustrative numerical example of some of the key tradeoffs of the model. Section 1.3 presents the general model and equilibrium solution concept. Section 1.4 solves the model for the case in which agents in both occupations work in spot markets and highlights the tensions in the model among fertility, labor supply, and occuapation choice. Section 1.5 introduces occupational amenities and key comparative statics with respect to their cost. Section 1.6 develops a model in which agents are heterogeneous in both schooling ability and home productivity. Section 1.7 discusses theoretical limitations of the model and extensions for future work. Section 1.8 presents empirical evidence consistent with the model's predictions, and Section 1.9 concludes.

1.2 The Model Simplified: A Numerical Illustration

I first describe a simplified numerical example that illustrates some of the basic tradeoffs in the model among fertility, labor supply, marriage matching, and occupation choice. Consider a continuum of recent college graduates, equally split between men and women, who spend two periods making occupation, marriage market, labor supply, and fertility decisions. The agents vary along two dimensions. Each has a cost of schooling $a_i \sim U([0, a_{max}])$, which includes both monetary and effort costs and is distributed identically for men and women. a_{max} is sufficiently large that the majority of individuals of each gender will always prefer not to invest in schooling. Each agent also has a home productivity α_i, which is the amount of child-related home production he or she can complete in a unit of time. For this example, all women have home productivity $\alpha_j = 1$ while all men have home productivity $\alpha_i = \alpha \in [0, 1]$.

The model has two periods (Figure 1.1). In the second period, agents participate in a transferable-utility marriage market and make fertility and family labor supply decisions. In the first period, agents choose one of two occupations, "Hi" or "Lo," in which to work in the second period. Individuals in occupation Hi earn wages $w_{2m} = w_{2f} = 2$ and individuals in occupation Lo earn $w_1 = 1$. Entering occupation Hi requires not working in occupation Lo in period 1, going to school, and paying direct cost a_i. I assume a rational expectations equilibrium; thus, agents do not regret their occupation choices in the second period.

For this numerical example I assume the utility function of Chiappori et al. (2009): each agent has utility

$$u_i = c_i \cdot q$$

where c_i is private consumption and $q = e + \gamma \cdot 1_K$ is a household public good. The household public good is the sum of the market-purchased household public good e and the utility from having a child γ. A couple can choose to have a child ($1_K = 1$) or have no child ($1_K = 0$). Agents

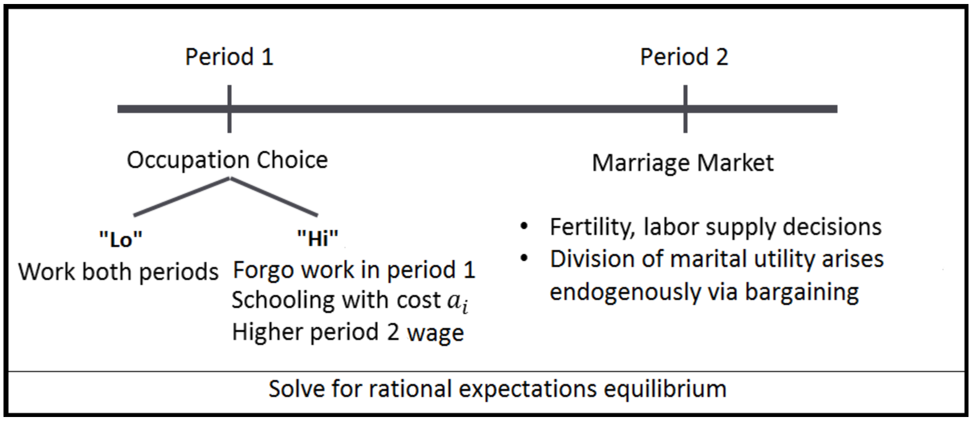

Figure 1.1: Model outline and timing.

each have a unit of time to divide between market work and child-related home production. A child requires home production $0 \leq \tau \leq 1$ which can be split between mother and father at the couple's discretion but can be provided by no other person.[4] The total cost of investment in the first period, including both schooling costs and forgone utility, is $a_i + \frac{w_i^2}{4}$, which is distributed identically for men and women.[5] I assume that $\gamma = 1.5$ so that $\gamma > w_{1.}$

The model is solved by backward induction, assuming the marriage market is in equilibrium conditional on first period occupation choices. Since utility is transferable between spouses, a married couple consisting of man i and woman j maximizes the sum of their utilities $u_i + u_j$ in the second period. Because the gains from children exceed the wages of individuals in occupation Lo ($\gamma > w_1$) and men's home productivity is weakly less than women's ($\alpha \leq 1$), couples including women in occupation Lo always have a child and these wives always provide child-related home production.[6] Couples including women in occupation Hi face two decisions: whether to have a child and, if so, which parent provides home production.

[4]Formally, it must hold that $\alpha h_i + h_j = \tau$ where h_i is time spent by the husband on child-related home production and h_j is time of the wife.

[5]Unmarried agents have no children, work only in the labor market, and split their income between the household public good and private consumption.

[6]The opportunity cost of providing a unit of home production for women in occupation Lo is w_1, which is always weakly less than both her husband's opportunity cost (either $\frac{w_1}{\alpha}$ or $\frac{w_2}{\alpha}$) and the gain in marital public good from having a child, γ.

In the analysis below, I consider three sets of parameters that illustrate the range of equilibrium matching and investment outcomes. Table 1.1 presents the career choices, marriage matching patterns, and utility values achieved in equilibrium for each of these cases. Each set of parameters yields a unique equilibrium in which less than half of the men choose occupation Hi by assumption and men outnumber women in occupation Hi. Thus, some men in occupation Lo must marry women in occupation Lo, and some men in occupation Hi must marry women in occupation Lo. This is sufficient to identify equilibrium payoffs for men in occupation Hi and to derive the gain in utility for men and women from investing and entering occupation Hi.[7]

In couples with both spouses in occupation Lo, the husband and wife have equal earning power, but the wife provides all of the child care since she is weakly more productive in the home. For this example I assume that the couples in occupation Lo divide marital utility equally.[9] A man in occupation Hi who marries a woman in occupation Lo generates additional marital utility due to his higher wage. Since women in occupation Lo always provide child-related home production, they contribute the same combination of income and home production to marriage with both types of husbands, and the husband in occupation Hi gets to keep the additional surplus he generates in marriage. Since some men in occupation Hi always marry women in occupation Lo, this bargaining identifies the utility received by men in occupation Hi in all cases.

In contrast, a woman in occupation Hi faces a dilemma. If men have low home productivity, a woman in occupation Hi will either not have a child or provide all child-related home production regardless of the occupation of her spouse. Thus, she marries the man with higher wage, and positive assortative mating on occupation is the stable marriage matching. However, she loses some of the benefit of her high wages since she either spends part of her time in child care or forgoes having children. If men are productive in the home, she has the choice of marrying a man

[7]In the general model presented in the next section, there are regions of the parameter space in which men and women each constitute half of occupation Hi. This occurs when required home production τ is very small or men and women are equally productive in the home ($\alpha = 1$).

[9]I assume throughout that everyone marries. In the general model, any split of marital utility for a couple in occupation Lo that gives both spouses at least their utility from being unmarried satisfies the conditions of equilibrium.

Table 1.1: Outcomes for Parameterized Model

	Case 1	Case 2	Case 3
Total required home production (τ)	0.5 (Moderate)	0.5 (Moderate)	0.85 (High)
Productivity of men (α)	0.1 (Low)	0.8 (High)	0.1 (Low)
Utility of Couples			
Man Hi, Woman Hi			
Child, Woman Provides Care	**5.06**	**5.06**	3.61
Child, Man Provides Care[8]	1.82	4.52	1.00
No Child	4.00	4.00	**4.00**
Man Lo, Woman Hi			
Child, Woman Provides Care	**3.06**	3.06	1.96
Child, Man Provides Care	1.82	**3.75**	1.00
No Child	2.25	2.25	**2.25**
Man Hi, Woman Lo	4.00	4.00	3.33
Man Lo, Woman Lo	2.25	2.25	1.76
Division of Utility in Second Period			
Utility of Agents in Occupation Lo	1.13	1.13	0.88
Gains to Hi for Men	1.75	1.75	1.57
Utility of Men in Occupation Hi	2.88	2.88	2.45
Gains to Hi for Women			
Married to Men in Occupation Hi	**1.06**	1.06	**0.67**
Married to Men in Occupation Lo	0.81	**1.50**	0.49
Utility of Women in Occupation Hi			
Married to Men in Occupation Hi	**2.19**	2.19	**1.55**
Married to Men in Occupation Lo	1.94	**2.63**	1.37
Percent Occupation Hi who are Women	35%	46%	24%
Composition of Married Couples in Equilibrium Marriage Matching			
Man Hi and Woman Hi	16%	0%	8%
Man Hi and Woman Lo	14%	30%	18%
Man Lo and Woman Hi	0%	25%	0%
Man Lo and Woman Lo	70%	45%	74%

Parameterization values are for the spot market model presented in Section 1.2. The wage values are $w_{2m} = w_{2f} = 2$ and $w_1 = 1$ and the utility from children is $\gamma = 1.5$. The maximum cost of schooling used to compute the distribution of couples is $a_{MAX} = 5$. **Bold** indicates the choice of fertility and home production that maximizes the utility of the couple or the marriage market equilibrium that maximizes total surplus.

in occupation Hi and still providing home production (or not having a child) or marrying a man in occupation Lo who will provide child care and allow her to work full time in the market. If men are sufficiently productive in the home, she marries the man in occupation Lo and negative assortative mating is the stable marriage matching. However, if her husband is less productive in the home than a woman in occupation Lo, their total marital utility is less than a couple in which the man is in occupation Hi and the woman in occupation Lo.

For the parameter values in Table 1.1, therefore, a high-wage woman always provides less incremental surplus to a marriage with either type of spouse than does a high-wage man marrying a woman in occupation Lo. Women receive less utility from entering occupation Hi than men, and thus there are fewer women than men in occupation Hi for each of the three sets of parameter values. Although women are more productive in the home and have equal nominal costs and wage benefits from entering occupation Hi, they achieve lower utility in equilibrium in each case.

- Case 1: $\alpha = 0.1$ (Low), $\tau = 0.5$ (Moderate)

In Case 1, required home production is moderate and men have relatively low home productivity. Women in occupation Hi provide greater incremental utility by marrying men in occupation Hi (from which they obtain utility 2.19) than by marrying men in occupation Lo (from which they obtain utility 1.94), so positive assortative mating is the stable marriage matching. The gain in second period utility from a woman entering occupation Hi is 1.06 and the gain for men is 1.75. All individuals who have a cost of investment less than or equal to these values enter occupation Hi.[10] Women constitute about a third of the individuals in occupation Hi, and therefore approximately half of the men in occupation Hi marry women in occupation Hi.

- Case 2: $\alpha = 0.8$ (High), $\tau = 0.5$ (Moderate)

In Case 2, required home production remains moderate, but men are more productive in the home than in Case 1. Men have the same payoffs and gains from investment as in Case 1. However, men in occupation Lo now provide child care in marriages with women in occupation Hi. Thus,

[10] Recall that the cost of investment $a_i + \frac{w_1^2}{4}$ includes both the individual cost of schooling and forgone earnings.

women have both greater incentive to marry men in occupation Lo and to choose occupation Hi. Negative assortative mating is the resulting marriage market equilibrium: each person choosing occupation Hi marries a spouse in occupation Lo. Since women in occupation Hi work full-time in the market and men are productive in the home, women in occupation Hi achieve only slightly lower utility than men in occupation Hi. Men still outnumber women in occupation Hi, but women constitute a higher fraction of occupation Hi (46%) than in Case 1 (35%).

- Case 3: $\alpha = 0.1$ (Low), $\tau = 0.85$ (High)

In Case 3, home productivity of men returns to its original low level, but the required level of home production increases compared to Case 1. The opportunity cost of child care in this case is so high that women in occupation Hi choose to remain childless. Thus, the high wages that women in occupation Hi bring to marriage are offset by the loss of utility from children, and women in occupation Hi are not much more attractive spouses than women in occupation Lo. Positive assortative mating is the stable marriage matching, and there is minimal incentive for women to choose occupation Hi. The fraction of women in occupation Hi (8%) is less than in Case 1 (14%).

This simple example illustrates some of the key dynamics of the model. In these three examples, women in occupation Hi spend part of their time in child care, forgo children, or outsource home production to men less efficient in the home than women.[11] Thus, they always receive less surplus from entering occupation Hi than men, who reap the full benefit from their increased wage. A decrease in required home production τ or an increase in men's home productivity α increases the gains to entering occupation Hi for women by altering fertility decisions, the division of home production within the family, and the equilibrium marriage matching.

The remainder of the paper explores the impact of changes in wages (Section 1.4) and the costs of occupational amenities (Section 1.5) on the investment and marriage market dynamics presented in this example. When individuals are heterogeneous in home productivity within

[11] The symmetric case in which $\alpha = 1$ is considered in the general model.

gender (see Section 1.6), women in occupation Hi may marry men in both occupation Lo and Hi in equilibrium even if they are outnumbered in occupation Hi, which corresponds more closely to empirical patterns presented in Section 1.8.

1.3 The Model

In this section I present the general model and equilibrium concept. The timing of the model is the same as outlined in Section 1.2 and in Figure 1.1. I again assume that there are a unit mass of men and a unit mass of women who differ in both their ability in schooling a_i and their home productivity α_i. Individuals may differ in home productivity between and within genders due to a combination of physiological differences, individual skill in and enjoyment of home production, social or cultural norms (Fernández et al., 2004), biological constraints on fertility (Siow, 1998), or the available home production technology (Greenwood et al., 2005). Proofs of all results are provided in Appendix A.

1.3.1 Family Production and Marital Surplus Division

I assume a transferable utility marriage market as in the seminal work of Becker (1973). The appropriateness of transferable utility in modeling family decision-making is a topic of active debate (see e.g. Lundberg and Pollak., 1996; Ashraf, 2009). Nonetheless, it is attractive in this setting for two reasons. First, it ensures that the marriage market equilibrium is unique, whereas when utility is non-transferable there may be many stable marriage matchings (Roth and Sotomayor, 1992). The division of marital surplus in a transferable utility framework via *ex post* bargaining provides clear intuition for the role of bargaining in surplus division without needing to model the relative bargaining power of the two sides of the market (Chiappori, 1992).

1.3.1.1 Utility of Individuals and Couples

By a classic result of Bergstrom (1989), a necessary and sufficient condition for transferable utility in a matching market is that agents have generalized quasi-linear utility.[12] I assume utility of this form with one marital public good q and one private good c_i

$$u_i = c_i \cdot G(q) = c_i \cdot G(e + \gamma \cdot 1_K) \tag{1.1}$$

where $G(q)$ is increasing and concave.[13] As in Section 1.2, the marital public good q is equal to the sum of a market-purchased public good e and utility from a child γ if a couple chooses to have one $(1_K = 1)$.

Because utility is transferable, a married couple with woman i and man j maximize the sum of their utilities $\eta_{ij} = \max\{u_i + u_j\}$. The following proposition is standard in the literature (see e.g. Chiappori et al. (2007)).

Proposition 1. *When agents have utility of the form in Equation 1.1, the total utility of married couple consisting of man i and woman j can be written as $\eta_{ij} = f(W_i + W_j + \gamma \cdot 1_K)$ where f is increasing and convex and $W_i + W_j$ is the total income of the couple.*

Single individuals cannot have a child, and their utility is $\eta_{i,0} = f(W_i)$ where W_i is individual i's income.

The total utility of a married couple η_{ij} satisfies $\frac{\partial^2 Z_{ij}}{\partial W_i \partial W_j} > 0$, which is the classic Becker condition for positive assortative mating on earnings (Becker, 1973). All else equal, high-earning and highly-educated individuals prefer to marry one another in the marriage market equilibrium. This assumption is consistent with the extensive literature documenting the increase in educational homogamy in the United States over the past sixty years (Blossfeld and Timm, eds, 2003; Schwartz and Mare, 2005; Mare, 1991; Rose, 2001).

[12] Generalized quasi-linear utility has the form $u_i(c^i, q) = f_i(c^i_{-1}, q) + c^i_1 G(q)$ where $\mathbf{c^i}$ is a vector of n private goods, $\mathbf{q}$ is a vector of m marital public goods, G and f are positive, increasing, concave functions, $G(0) = 1$, and $f_i(0) = 0$, and $q^i_1 > 0$ for all i (Chiappori et al., 2007).

[13] Because I consider only equilibria where all agents marry, I am not interested in individual variation in the utility from marriage. Thus, I normalize the individual portion of the utility function to $f_i(q) = 0$.

In a transferable utility marriage market, bargaining power arises endogenously after the unique equilibrium is determined. For marriage to be individually rational, each individual must get at least his outside option, which is the utility from being single. Thus, agents bargain to split the marital surplus

$$Z_{ij} = \eta_{ij} - \eta_{i,0} - \eta_{j,0}.$$

1.3.1.2 Labor Supply and Fertility Decisions

In each period, each agent has a unit of time to divide between home production and work. All non-child-related home production can be purchased in the market, so only couples with children must make labor supply and home production decisions. A couple can choose whether to have a child. If the couple has a child, the spouses are required between them to supply total home production $\tau \in [0,1]$. Any additional parental time has no additional benefit for the child, and thus any time not spent producing τ is spent in the labor market.

Unlike much of the literature on family labor supply and the market for child care, I do not allow parental time spent on child care to be a function of wages or the price and quality of child care available in the market (e.g. Blau and Hagy, 1998). My assumption that there is a fixed requirement for parental time that is independent of wages (conditional on having a child) captures the intuition that there is some portion of child care that cannot be outsourced to the market at any price. Empirical evidence does not dispute this assumption: time use data shows that educated parents have increased the time spent with their children even as their wages have risen and as time spent on other forms of home production has decreased (Aguiar and Hurst, 2007; Guryan et al., 2008).[14]

Because marital surplus is increasing in the total income of the family, a couple with a child will choose the labor supply that maximizes total earnings. Let $W_i(t)$ be the earnings of individual i when he or she works time t in the market. A family of man i and woman j with home

[14] A more nuanced model that allows child quality to vary with parental time and the quality of market-purchased child care would be an interesting future endeavor.

productivities α_i and α_j and with a child thus has total income

$$W_i^* + W_j^* \equiv \arg\max_{t_i, t_j \in [0,1]} W_i(t_i) + W_j(t_j)$$
$$\text{s.t. } (1 - t_i)\alpha_i + (1 - t_j)\alpha_j = \tau$$

When both agents work in a spot market and earn wages w_i and w_j, all home production is provided by the agent with comparative advantage in home production, or a lower opportunity cost of time $\frac{w}{\alpha}$.[15]

A couple chooses to have a child if $f(W_i^* + W_j^* + \gamma) \geq f(W_i + W_j)$, where $W_i = W_i(1)$ is individual $i's$ earnings when working full-time in the labor market, or equivalently if the utility from a child is greater than the labor market opportunity cost ($\gamma > W_i + W_j - W_i^* - W_j^*$).

1.3.1.3 Equilibrium Matching and Marital Surplus Division

Following the literature on matching with transferable utility (Shapley and Shubik, 1971; Becker, 1973; Chiappori et al., 2009), I assume the marriage market equilibrium condition of *stability*. Shapley and Shubik (1971) prove that a matching in a transferable-utility marriage market is stable if and only if it maximizes total utility in the matching market.[16] When one side of the marriage market consists of only two types of men or of women, it is straightforward to show that a matching is stable if for all couples ij and kl matched in the stable matching,

$$\eta_{ij} + \eta_{kl} \geq \eta_{il} + \eta_{kj}$$

After the stable matching is determined, the split of marital surplus between husband and wife arises endogenously via market bargaining power. Let U_i be the portion of the marital surplus Z_{ij} given to the husband in pairing ij and V_j be the surplus given to the wife. For there to be no blocking pairs, it must be that

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[15]If $\alpha_i < \tau$, agent i may exhaust his time allocation and still not complete all home production. In this case, the other spouse completes the remaining home production. Formally, we require the assumption that $\tau < \alpha_i + \alpha_j$. In practice, τ will always be less than the home productivity of the least productive woman.

[16]Let M be the set of men, W be the set of women, and $\emptyset$ be "unassigned." A matching is a pair of mappings $\mu : M \rightarrow \{W \cup \emptyset\}$ and $\nu : W \rightarrow \{M \cup \emptyset\}$ such that $\mu(m) = w$ if and only if $\nu(w) = m$.

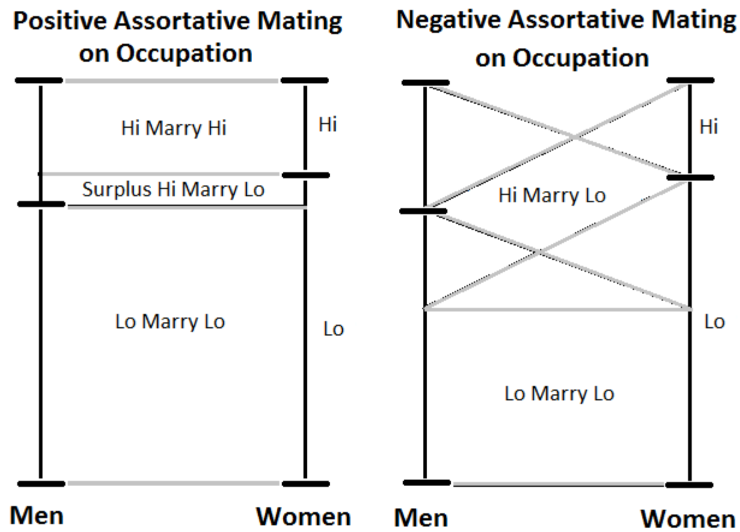

Figure 1.2: Two possible marriage market equilibria: positive assortative mating (left) and negative assortative mating (right).

$$U_i + V_j \geq Z_{ij} \tag{1.2}$$

for all couples ij with equality if i and j are matched to each other in the stable matching (Shapley and Shubik, 1971; Becker, 1973; Chiappori et al., 2009). In order for everyone to marry, marriage must be individually rational for all agents, or that $U_i \geq 0$ and $V_j \geq 0$. Because couples in the model can choose not to have a child, there is always a surplus division in equilibrium in which marriage is individually rational for all agents.

Figure 1.2 illustrates the two possible equilibrium marriage matchings in the special case in which agents are differentiated only by their occupation and men in occupation Hi weakly outnumber women in occupation Hi.[17] When positive assortative mating is the marriage market equilibrium, individuals in occupation Hi marry and individuals in occupation Lo marry. If there is a surplus of individuals in occupation Hi of one gender, they marry individuals in occupation Lo of the other gender. If negative assortative mating on occupation is the equilibrium matching, all individuals in occupation Hi marry individuals in occupation Lo and the remaining individuals in

[17] Recall that an assumption of the model is that a minority of agents of each gender invest in schooling to enter occupation Hi.

occupation Lo marry.

The system of inequalities defined by Equation 1.2 gives a unique solution to the *gains* in marital surplus from entering occupation Hi for both men and women. However, the total utility received by agents in the market may not be uniquely identified. For example, when home productivity does not vary within gender as in Section 1.2, any division of surplus between couples in occupation Lo satisfying $U_L + V_L = Z_{LL}$ with U_L, $V_L \geq 0$ satisfies the conditions for equilibrium. The fraction of Z_{LL} received by men can be thought of as the degree to which the market favors men but does not impact equilibrium marriage market outcomes, fertility decisions, or occupation choices.

A key characteristic of this endogenous surplus division is that agents who are relatively scarce in the market have bargaining power and extract additional surplus they create in the match. If women in occupation Hi outnumber men in occupation Hi and positive assortative matching is stable, for example, women in occupation Hi keep the surplus that they generate in a match in occupation Hi above the surplus generated by the same man when matched with a woman in occupation Lo. When agents vary within gender in both occupation and home productivity, agents with high home productivity keep the additional surplus they generate from their home production efficiency when they are scarce.

1.3.2 Occupation Choice

In the first period, agents choose the occupation "Hi" or "Lo." Occupation Lo requires no investment in schooling: agents work in a spot market in both periods 1 and 2 for the hours of their choosing and earn a constant wage w_1. Alternatively, agents can invest in a period of schooling in period 1, forgoing wages and paying cost a_i, and enter occupation Hi. The earnings of men and women in occupation Hi are strictly higher than those of men and women in occupation Lo for all amounts of labor supplied ($W_i(t) > w_1 \cdot t$ for all values of t) but W_i may include nonlinearities. Section 1.5.1 presents a stylized framework for $W_i(t)$ when flexibility is costly.

Let η_L be the utility of an unmarried individual in occupation Lo, $\eta_{iH,0}$ be the utility of an unmarried male in occupation Hi, and a_i be man i's cost of schooling. $U_{i,H}$ and $U_{i,L}$ are the marital surplus received by a man with home productivity α_i in occupations Hi and Lo, respectively. Man i chooses to invest and enter occupation Hi if the total utility from investment is greater than or equal to the total utility from not investing and working in the first period.

$$U_{i,H} + \eta_{iH,0} - a_i \geq 2\eta_L + U_{i,L}$$

The expression for women is analogous.[18] Note that this defines a cutoff cost of schooling a_i^* such for all men with home production α_i, men with $a_i \leq a_i^*$ invest and enter occupation Hi and all others remain in occupation Lo.

1.3.3 Equilibrium

In a rational expectations equilibrium, agents need to correctly anticipate both the labor market and marriage market returns to each occupation. The marriage market returns are in turn a function of the occupations chosen by individuals in the market, as the division of marital surplus depends on the distribution of earnings-home producitivity pairs on each side of the marriage market. The conditions for equilibrium are thus as follows:

1. Given the utility in each occupation $U_{i,L} + 2\eta_{i,L}$ and $U_{i,H} + \eta_{iH,0}$ for each individual i, all individuals choose the occupation that provides higher utility. An indifferent individual enters occupation Hi.

2. Given the occupation choices of individuals in period 1, the marriage market equilibrium is stable.

Note that, as discussed in Subsection 1.3.1.3, the utility received by agents in equilibrium may not be uniquely identified. However, the marriage market matching is unique, and the system of equations generated by the inequalities 1.2 uniquely identifies the gain in utility for each agent from entering occupation Hi thus equilibrium occupation choices.

[18] There is no time discounting.

1.4 Occupations as Spot Markets

I assume for this section that both professions offer only spot market work with $w_{2m} \geq w_{2f} > \gamma > w_1$ where γ is the marital public good from a child. The assumption of spot market work is standard in the literature on family labor supply (Gronau, 1977).[19] The difference between the wages of men and women in occupation Hi may be due to a variety of non-labor-supply factors. Women may face discrimination (Bertrand et al., 2005), have a lower propensity to negotiate for pay (Babcock and Laschever, 2003), or may have a lower level of unobservable skill (Blau and Kahn, 2000).

I again assume that women and men differ between, but not within, genders in home productivity. All men have home productivity $\alpha_i = \alpha$ and all women have home productivity $\alpha_j = 1$. Note that while I allow for gender asymmetries in home production or market wage, the model nests the symmetric special case $\alpha = 1$ and $w_{2f} = w_{2m}$.

The following results illustrate the tradeoffs between spouse choice, fertility, and family labor supply and generalize the intuition presented in the numerical example in Section 1.2.

Lemma 1. *When men in occupation Lo never have a comparative advantage in home production* ($\alpha \leq \frac{w_1}{w_{2f}}$)*, positive assortative matching is the stable outcome.*

While the mathematical proof is immediate, I highlight Lemma 1 as a result that is both useful for intuition and used repeatedly in proofs that follow. It captures a straightforward observation: in the absence of a reduction in the opportunity cost of a child from "marrying down," the complementarities between individuals in occupation Hi make positive assortative matching the stable marriage market outcome. Women in occupation Lo always have a comparative advantage in home production, so the set of parameters for which Lemma 1 holds is defined by when men in occupation Lo do not have a comparative advantage in home production relative to women in occupation Hi.

[19] To ensure that there are always some women who invest and enter occupation Hi, I assume w_{2f} is sufficiently large that $\eta_{LL} - \eta_{LA} > \eta_A$ and $\eta_{AL} - \eta_{AA} > \eta_A$. The simulation parameters used in Section 1.2 satisfy these inequalities.

1.4.1 Equilibrium Marriage Matching, Fertility, and Labor Supply

Theorem 1 gives the key matching, labor supply, and fertility dynamics of the model when agents in both occupations work in spot markets. This generalizes the example in Section 1.2.

Theorem 1. *Fix wages and gains from children γ, and let $w_{2m} \geq w_{2f} > \gamma > w_1$.*

1. *There is a continuous function $\hat{\alpha}(\tau)$ such that for $\alpha > \hat{\alpha}(\tau)$, negative assortative matching on occupation is the stable marriage matching. In this region, all individuals in occupation Hi marry individuals in occupation Lo and all home production is provided by men and women in occupation Lo. For $\tau > \frac{\gamma}{w_{2f}}$ and $\alpha \leq \hat{\alpha}$, there is positive assortative matching on occupation but women in occupation Hi do not have a child. For $\tau \leq \frac{\gamma}{w_{2f}}$ and $\alpha \leq \hat{\alpha}$, the stable matching is positive assortative on occupation, all couples have a child, and all home production is provided by women.*

2. *$\hat{\alpha}$ is increasing in τ when women in occupation Hi do not have a child. When the derivative of the surplus function, f', is convex, $\hat{\alpha}$ is decreasing in τ for $\tau \leq \frac{\gamma}{w_{2f}}$.*

Figure 1.3 shows the equilibrium marriage, fertility, and labor supply decisions as a function of total home production required by children τ and home productivity of men α for wage parameters $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, and $w_1 = 1$.

When men are highly productive in the home (α is large), near gender symmetry is achieved. If total production required τ is small, women have a high opportunity cost of providing childcare, but τ is sufficiently small that it is still optimal for high earners to marry each other and for women in occupation Hi and women in occupation Lo to provide home production. When τ is large, the opportunity cost of women in occupation Hi providing childcare is sufficiently large that it is optimal for both men and women in occupation Hi to marry men and women in occupation Lo so they can work full-time in the labor market.

When women always have comparative advantage in the home (α is low), women provide all child-related home production. If the total time required for a child is large, women in occupation Hi forgo having a child. As the time required for children decreases, the gain from children

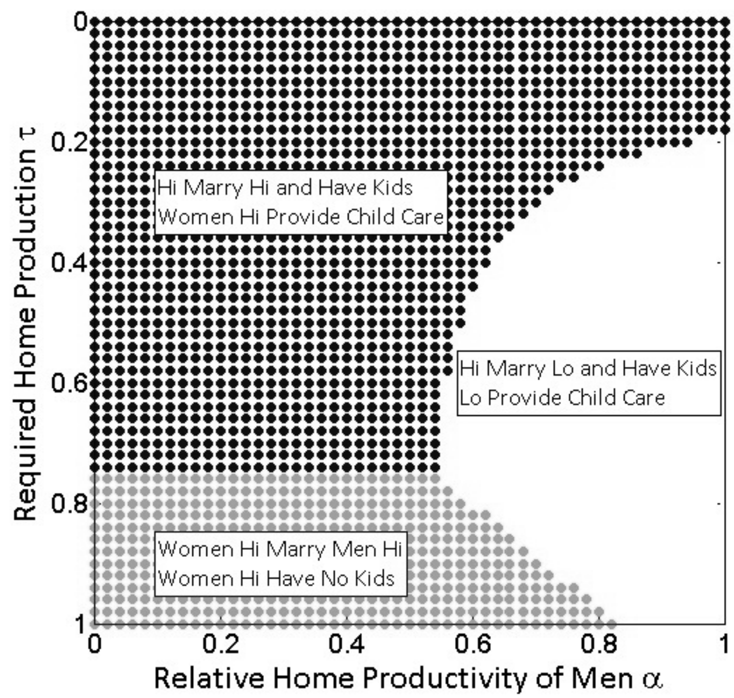

Figure 1.3: Equilibrium matching, labor supply, and fertility decisions in the spot market model as a function of home production parameters. Wage and child utility parameters are $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, and $w_1 = 1$.

outweighs the opportunity cost of their care, and women in occupation Hi have children and spend the remainder of their time in the labor market.

The negative derivative of $\hat{\alpha}$ when women in occupation Hi have a child documents the tradeoff between time required for childcare and spouse substitutability: the larger the opportunity cost for a woman in occupation Hi to raise a child, the more willing are men and women Hi to marry lower-earning spouses so that they can both spend their time in the labor market. The sufficient condition that the derivative of the total utility function, f', is convex recalls the literature on precautionary savings (Kimball, 1990), although ours is not a necessary condition. It captures the intuition that the gains from positive assortative mating on earnings must be "sufficiently large," or equivalently that f is "sufficiently convex." The utility specification used in Section 1.2 is on the boundary of satisfying this condition: the utility of a married couple is quadratic in total income and thus has a zero second derivative.

Theorem 1 captures intuition from two strands of the marriage market literature. The negative slope of the cutoff between positive and negative assortative mating $\hat{\alpha}$ follows the insight of Becker (1973) that the equilibrium of a marriage market is a function of the tradeoff between complementarity and substitutability of spouses in producing marital surplus. I also formalize and generalize the comment of Chiappori et al. (2009) that a switch from the social norm that women always provide childcare to an equitable norm in which men and women are equally efficient in home production introduces negative assortative matching for sufficiently large values of required home production τ.

1.4.2 Investment and the Gender Ratio in the High-Earning Occupation

To complete the equilibrium, I need to verify that the surplus division from the marriage market is consistent with the investment decisions made by agents in the first period of the model. When home productivity differs only by gender, marriage market surplus is a function of occupation and gender, and thus the equilibrium surplus division depends only on the ratio of men in occupation

Hi to women in occupation Hi. Theorem 2 solves for the ratio of men to women in occupation Hi as a function of the underlying home production parameters and wages and verifies that it is consistent with the equilibrium division of marital surplus.

Theorem 2. *Men in occupation Hi always weakly outnumber women in occupation Hi. The fraction of individuals in occupation Hi who are women is minimized when $\tau = \frac{\gamma}{w_{2f}}$ and positive assortative matching is stable. This fraction is increasing in α, increasing in τ when women in occupation Hi do not have a child and positive assortative matching is stable, and weakly decreasing in τ when they do have a child and the derivative f' is convex.*

Because home production ability does not vary within gender, the fraction of women in occupation Hi is given by

$$FW = \frac{a_j^*}{a_i^* + a_j^*}$$

where a_j^* is the cutoff cost of schooling below which women enter occupation Hi and a_i^* is the equivalent cutoff for men. The fraction of individuals in occupation Hi who are women is shown in Figure 1.4 for wage values $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, and $w_1 = 1$.

A sufficient assumption for men in occupation Hi to weakly outnumber women in occupation Hi is that men are weakly less efficient in home production than women. Because there are thus always men in both occupation Hi and occupation Lo who marry women in occupation Lo, men's gains to entering occupation Hi are always given by $\eta_{LA} - \eta_{AA} - \eta_A$. This is only a function of the wage of men in occupation Hi, w_{2m}, the wage of individuals in occupation Lo, w_1, and the total required child-related home production τ.

The gains to entering occupation Hi for women are a more complicated function of fertility decisions and home production parameters. When positive assortative matching is stable, the gains to investment for women are a function of both the time required for home production τ and the decision to have a child. When negative assortative matching is stable, women's gains to investment are increasing in the home productivity of men. The gains to entering occupation Hi, excluding individual cost parameters, are shown in Figure 1.5 for both men and women.

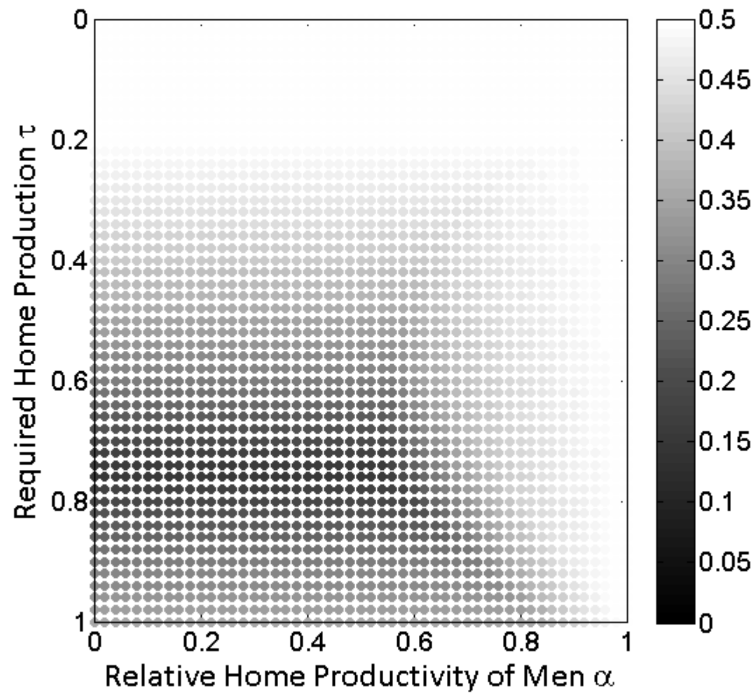

Figure 1.4: Fraction of Occupation Hi who are women in the spot market model as a function of home production parameters. Wage and child utility parameters are $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, and $w_1 = 1$.

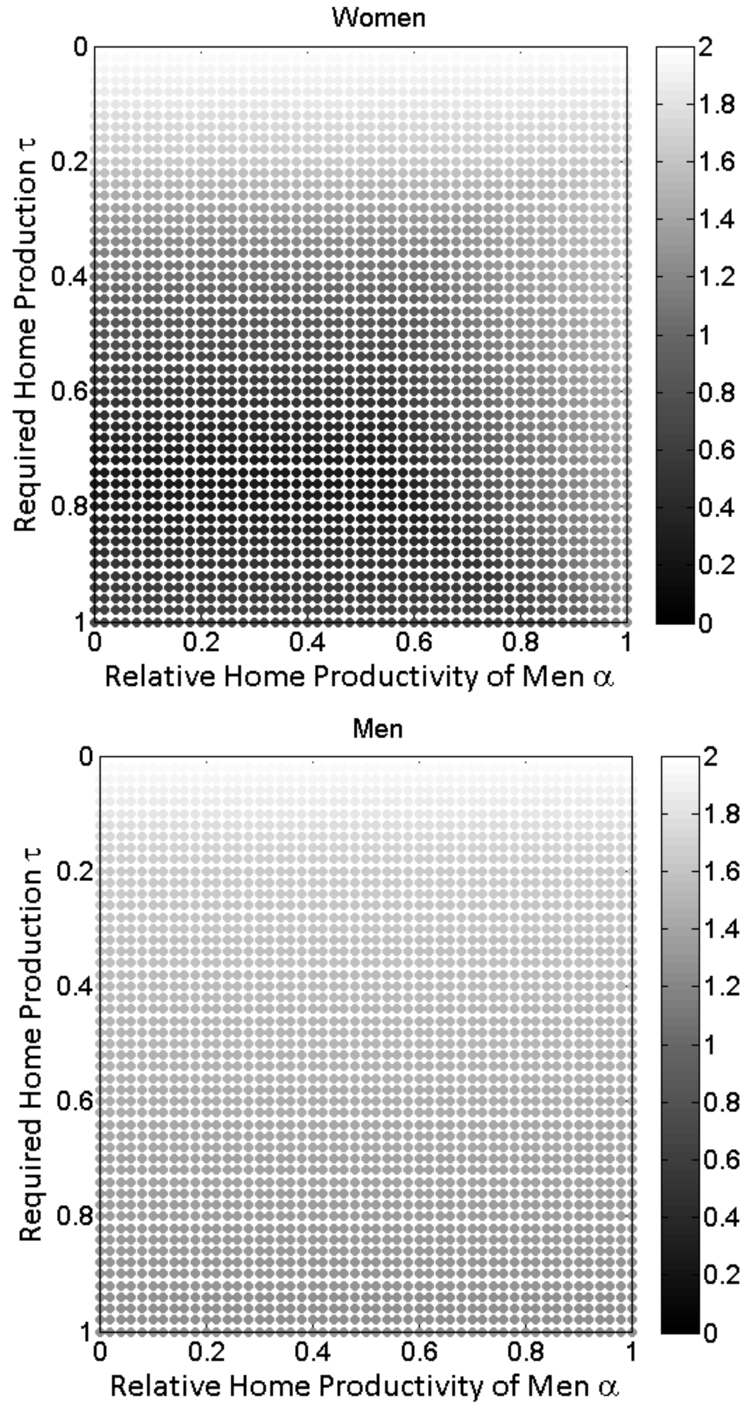

Figure 1.5: Utility gains to entering Occupation Hi by gender in the spot market model as a function of home production parameters. Wage and child utility parameters are $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, and $w_1 = 1$.

When men and women in occupation Hi receive the same wage ($w_{2m} = w_{2f}$), for symmetric home productivity ($\alpha = 1$) or for τ small, the unique equilibrium is for an equal number of men and women to enter occupation Hi. In this case, if positive assortative mating is the stable marriage matching, agents in occupation Hi split marital surplus equally. This equilibrium persists if women's wages in occupation Hi are sufficiently close to men's and τ is small. For more on this equilibrium, see Chiappori et al. (2009).

In the region of the parameter space in which women in occupation Hi have no child, an increase in required childcare time τ *increases* the incentives for women to enter occupation Hi. As τ increases, women in occupation Lo must invest more time in childcare and reduce their market work while women in occupation Hi are unaffected. This increases the surplus that women in occupation Hi bring to marriage and receive in bargaining.

1.4.3 Impact of Wage Changes on Equilibrium Matching and Investment

There is a subtle comparative static effect of a change in wage on the equilibrium marriage market and investment decisions. While an increase in the wages of men in occupation Hi unambiguously increases the region in which positive assortative matching is stable, the impact of an increase in the wages of women in occupation Hi depends on the wage difference between men in occupation Hi and occupation Lo.

Theorem 3. *An increase in the wages of men in occupation Hi, w_{2m}, increases the cutoff for negative assortative mating $\hat{\alpha}$. An increase in the spot wage of women in occupation Hi 1) increases the region in which women in occupation Hi have no children and 2) decreases the cutoff for negative assortative mating $\hat{\alpha}$ if $\tau \leq \frac{\gamma}{w_{2f}}$ and $\frac{\partial f_{LL}}{w_{2f}} < \frac{\partial f_{AL}}{w_{2f}}$. An increase in the wages of women in occupation Hi increase the fraction of individuals in occupation Hi who are women.*

An increase in the spot wage of women in occupation Hi produces dynamics similar to those described by Feyrer et al. (2008): more women invest and enter occupation Hi, and fertility of women in occupation Hi decreases if men do not participate in home production. The impact on the marriage market equilibrium is ambiguous: while the opportunity cost of children increases and thus negative assortative mating is more attractive, higher spot wages also increase the complementarities between high earners. Which effect dominates is a function of the wage difference between men in occupation Hi and in occupation Lo and the convexity of f, the utility function of married couples.

Note that an increase in women's wages w_{2f} unambiguously increases the utility of women in occupation Hi.

1.5 Adding Occupational Amenities

1.5.1 Modeling Flexibility

Models of family labor supply and educational investment traditionally assume that agents face a spot labor market (Gronau, 1977), and that an investment in education results in a higher future spot market wage. I expand this framework to include a stylized model of an occupational amenity in the spirit of Rosen (1986). Formally, the high-paying occupation (Hi) will exhibit nonlinear opportunity costs of time from child-related home production. Colloquially, I refer to this disamenity as *inflexibility*.

I model flexibility as follows: individuals who have invested to become Hi have a choice of two types of work. The first option is for Hi to work in "firms." Workers in firms are more productive; however, in order to reap the benefits of working in firm, the worker must provide minimum labor supply b or higher. The wages paid by the firm are w_{2m} for men and w_{2f} for women with $w_{2m} \geq w_{2f} > \gamma > w_1$. If the worker cannot fulfill the requirement for hours b, she works in the spot market. To compensate for the disamenity of imposing a minimum hours of work, firms compensate workers with wage Δ above the spot market wage. Individuals in occupation Hi always make more than individuals in occupation Lo, or $w_{2f} - \Delta > w_1$. Formally, earnings in occupation Hi as a function of time worked t, $W_i(t)$, are now a piecewise linear function. For

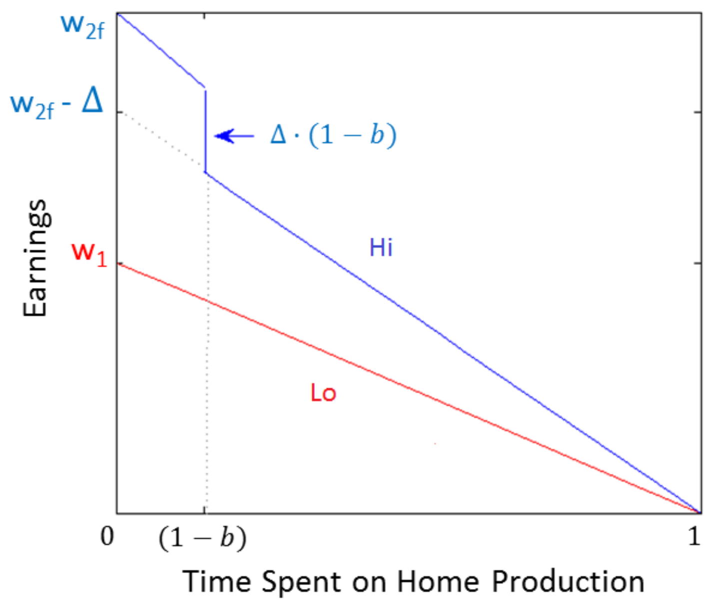

Figure 1.6: Earnings as a function of labor supply for Occupation Hi and Occupation Lo.

women, they are

$$W_j(t_j) = \begin{cases} w_{2f} \cdot t_j & \text{if } t_j \geq b \\ (w_{2f} - \Delta) \cdot t_j & \text{if } t_j < b \end{cases} \tag{1.3}$$

and similarly for men. The decrease in wage at the point b induces a discrete jump in earnings of size Δb. An illustration of earnings as a function of time is given in Figure 1.6.

The discrete cost of flexibility $b\Delta$ in this stylized model reflects career costs of family that are not proportional to labor supply. Goldin and Katz (2011) find substantial variation in the magnitude of these nonlinearities among mothers in medicine, business, and law; these are discussed further in Section 1.8.

A functional form that results in substantively similar results is one in which firms pay women $w_{2f}g(t_i)$ and men $w_{2m}g(t_i)$ where g is increasing and concave, $g^{-1}(0) > 0$, and $g'(1) > 1$. Such a functional form could arise from a combination of fixed costs and substantial (but decreasing) learning by doing.[20] I assume the functional form in Equation 1.3 because it allows

[20] The one substantive difference is that for α close to 1 and w_{2f} close to w_{2m}, the concave function $w_{2i}g(t_i)$

for straightforward comparative statics with respect to b and Δ.

1.5.2 Optimal Labor Supply of Couples

Introducing the occupational amenity flexibility substantially complicates the optimal labor supply and equilibrium matching of the market but gives important insight in to the relationship between occupational characteristics, home production technology, and marriage market outcomes. Theorem 4 proves that the nonlinearities in earnings introduced by occupational amenities can result in high-earning couples sharing child-related home production. To capture the intuition that b represents a long-hours job, I assume here that the minimum hours at the firm b is sufficiently large such that if two individuals in occupation Hi can share childcare and still work in the firm, they do so.[21]

Theorem 4. *When $\Delta > 0$, there are values of (τ, α) such that the optimal labor supply of couples that include women in occupation Hi is to share home production with men in occupation Hi or men in occupation Lo. The area of the (τ, α) parameter space in which sharing is optimal is increasing in the cost of flexibility Δ.*

The discrete jump in the budget constraint for women in occupation Hi implies that it can be income-maximizing for men and women to share childcare responsibilities even when the woman has a comparative advantage in home production (Figure 1.7). The husband contributes to home production until the higher opportunity cost of his time from the combination of higher wages and lower home productivity is no longer outweighed by the discrete loss of earnings from the woman purchasing flexibility.

A decrease in the minimum effective hours of firms b has an interesting two-fold effect for high-earning couples near the cutoff between sharing home production and having the woman purchase

results in more equal sharing of home production than does the functional form $W_j(t_j)$ in which women always provide home production up to $\tau = b$ before men provide any home production.

[21] In Appendix A, I show that the condition for this to hold is $b \geq \frac{w_{2f} + w_{2m} - \gamma}{w_{2f} + w_{2m}}$.

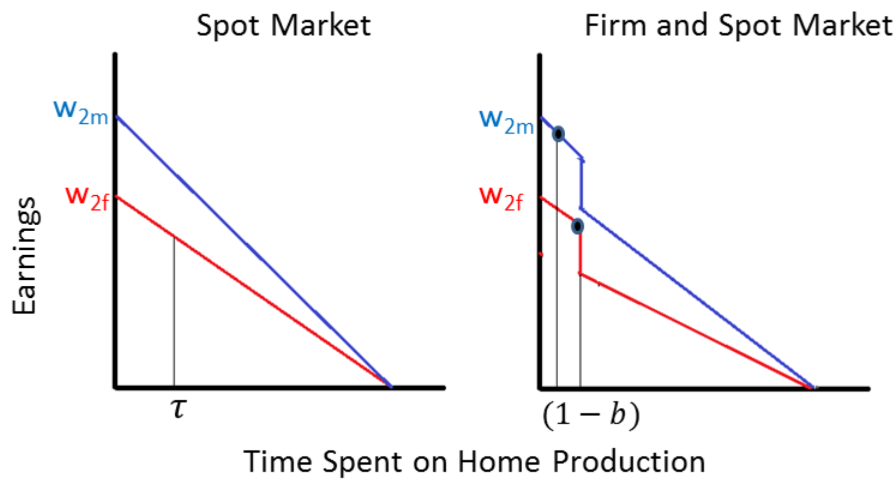

Figure 1.7: Optimal labor supply and time on home production for a couple in Occupation Hi when flexibility is costless (left) and costly (right).

flexibility: a decrease in b can result in a *decrease* in men's labor supply. This occurs when the couple switches from having the woman purchase flexibility and provide all home production to the couple sharing home production and both working in a firm.

1.5.3 Impact of Costly Flexibility on Equilibrium Matching, Fertility, and Occupation Choice

Theorems 5 and 6 are two of the main results of the paper. An increase in the cost of flexibility Δ has three main effects on marriage patterns, fertility, and occupation choice. Theorem 5 derives the comparative statics with respect to fertility and equilibrium marriage patterns. Increasing Δ decreases the threshold $\hat{\alpha}$ for negative assortative mating when women lawyers work in the spot market. An increase in Δ also increases the region of the parameter space in which women Hi have no children. This shift occurs on two margins: an increase in the cost of flexibility Δ increases the career cost of family for high-earning couples, thus reducing their fertility, and also results in a shift from negative assortative mating with children to positive assortative mating with couples in occupation Hi having no children.

Theorem 5. *An increase in the gains to firm work Δ decreases the cutoff for negative assortative*

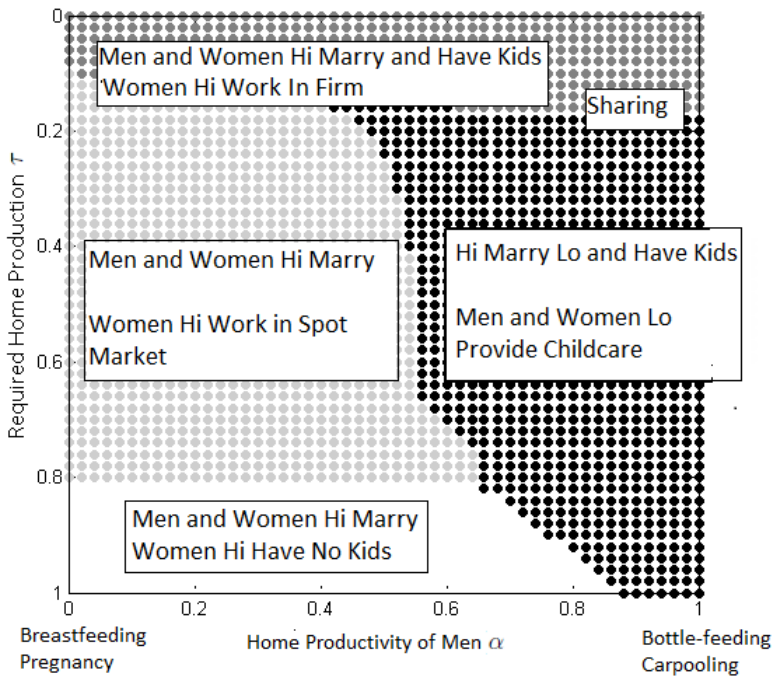

Figure 1.8: Equilibrium marriage matching, labor supply, and fertility when flexibility is costly as a function of home production parameters. Wage and child utility parameters are $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, $w_1 = 1$, $\Delta = 0.2$, and $b = 0.9$.

mating $\hat{\alpha}$ when women in occupation Hi work in the spot market and men in occupation Lo have time budget constraints that are not binding. An increase in the gains to firm work Δ increases the region in which women in occupation Hi have no child.

Figure 1.8 shows the equilibrium marriage, fertility, and labor supply outcomes with wages $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, and $w_1 = 1$. The cost of flexibility is $\Delta = 0.2$ and the minimum labor supply for the firm is $b = 0.9$. Comparing Figure 1.8 with Figure 1.3 shows the impact of costly flexibility on the equilibrium set of outcomes.

Theorem 6 completes this set of results by examining the impact of an increase in the cost of flexibility Δ on equilibrium occupation choice. An increase in Δ decreases the gains to entering occupation Hi for women when women in occupation Hi work in the spot market and does not impact the gains to entering occupation Hi for men. Thus, an increase in Δ unambiguously decreases the fraction of women in the high-paying occupation when women in occupation Hi work in the spot market.

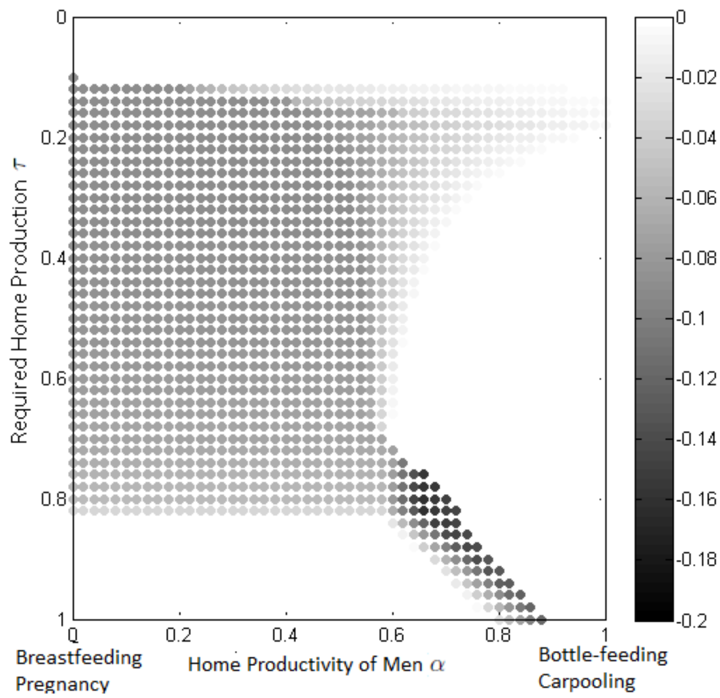

Figure 1.9: Decrease in fraction Occupation Hi who are women when flexibility is costly compared to costless flexibility as a function of home production parameters. Wage and child utility parameters are $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, $w_1 = 1$, $\Delta = 0.2$, and $b = 0.9$ for costly flexibility and $\Delta = 0$ for costless flexibility.

Theorem 6. *Men in occupation Hi weakly outnumber women in occupation Hi. An increase in Δ decreases the fraction of individuals in occupation Hi who are women when positive assortative mating is the stable matching and women in occupation Hi work in the spot market.*

Figure 1.9 shows the decrease in the fraction of women in occupation Hi when the cost of flexibility is increased from $\Delta = 0$ to $\Delta = 0.2$. Wages are $w_{2m} = 2$, $w_{2f} = 1.8$, $\gamma = 1.5$, and $w_1 = 1$ and the minimum labor supply in the firm is $b = 0.9$.

1.5.4 Comparison of Changes in Wages and Costs of Flexibility

Comparing Theorems 5 and 6 with Theorem 3 makes clear the difference between the impact of spot wage changes and the impact of changes in the prices of amenities on marriage market, investment, and fertility decisions. An increase in the spot wage of women in occupation Hi increases both the opportunity cost of children and complementarities between high-earning women and men. More women enter occupation Hi and the labor supply of these women (almost always) increases, both through decreased fertility and more negative sorting in the marriage market.

An increase in the cost of flexibility, however, impacts equilibrium outcomes only through the opportunity cost of children. Decreasing Δ increases the utility of women in occupation Hi and the incentives of women to enter the high-paying occupation. However, it also results in more positive assortative mating among individuals in occupation Hi and higher fertility. Thus, a decrease in the cost of flexibility Δ may result in a *decrease* in the labor supply of women in occupation Hi as they switch from roles as primary breadwinners or members of childless couples to childcare providers with husbands in occupation Hi.

1.5.5 Impact of Changes in Hours Requirement b on Occupation Choice

While the model for the hours threshold b is not microfounded, it is still useful to contrast the impact of a change in Δ on investment incentives of women with a change in b. An exogenous decrease in b might be due to improvements in telecommunitions technology which allow agents to complete the same amount of work with fewer hours at the firm (Autor, 2001).

Theorem 7. *A decrease in required hours b increases the fraction of individuals in occupation Hi who are women only if women in occupation Hi share home production with their husbands.*

A decrease in b results in a shift of home production to the wife if she was previously providing the minimum labor supply required by the firm. This increases the utility of high-earning couples since women in occupation Hi have a weakly lower opportunity cost of time when sharing is the optimal division of home production. This results in more women investing to enter occupation Hi and also makes positive assortative mating a more attractive outcome. A decrease in minimum labor supply b thus impacts the fraction of women in occupation Hi for a different set of parameter values than does a decrease in the cost of flexibility Δ : decreasing b increases the utility of women in occupation Hi when they just miss the cutoff for working in the firm, whereas decreasing Δ

increases the utility of women in occupation Hi for women not close to the minimum hours required by the firm.

1.6 Adding Heterogeneity in Home Production Ability

Finally, I consider a stylized example in which men are heterogeneous in home production efficiency. When agents are heterogeneous in home productivity within gender, schooling ability and home productivity jointly determine optimal marriage and occupation decisions. The introduction of occupational amenities has an interesting, subtle effect on the interaction of these two parameters in occupation choice.

Assume that a small fraction of men q are endowed with high home productivity $\alpha' \leq 1$ and the remaining fraction $1-q$ have home productivity $0 \leq \alpha < \alpha' \leq 1$. Home productivity is distributed independently of schooling ability. All women continue to have home productivity $\alpha_f = 1$.

Theorem 8. *1. Assume that agents in both occupations work in spot markets. If negative assortative mating is the stable matching for men with high home productivity ($\alpha' > \hat{\alpha}$ from Theorem 1) and q is sufficiently small, then the fraction of men with high α ($\alpha_m = \alpha'$) who invest and enter occupation Hi is less than the fraction of men with low α ($\alpha_m = \alpha$) who invest. The disparity in investment is increasing in α' and increasing in w_{2f} if $\frac{\partial f_{LL}}{w_{2f}} < \frac{\partial f_{AL}}{w_{2f}}$.*

2. If τ,α, and α' are such that positive assortative mating with sharing of home production is the equilibrium outcome, the fraction of men with α' investing to enter occupation Hi is higher than the fraction of men with α who invest.

When men with high home productivity are scarce, they have a disincentive to enter occupation Hi, as they obtain surplus from providing home production for high-earning women and capture the gain in utility their high productivity generates. Spot markets thus encourage specialization in home or work. When high-earning couples share home production, agents receive additional surplus for being both high-earning and productive in the home. Thus, individuals with high home productivity are *more* likely to enter occupation Hi.

The model in which agents are drawn from a continuum of both schooling costs and home productivities is substantially more complicated to solve. The two-type model presented in this section captures the main intuitions with respect to marriage patterns and investment incentives of the multi-dimensional model. It is also straightforward to allow for men who are more productive than women in the home ($\alpha' > 1$).

1.7 Limitations of the Model

Two extensions of the current model would be valuable to explore in future work. The first is to explicitly model firms and allow wages and the costs of amenities to be endogenous outcomes of firm and home production technology. Such a model would be in line with existing literature on occupational amenities (see e.g. Goldin and Katz, 2011; Rosen, 1986) and would provide general equilibrium predictions of the impact of "family-friendly" policy on both firms and workers.

A second extension is to allow investment in both home productivity and schooling in the first period. As women's wages increase, men who are highly productive in the home would thus arise endogenously. This would be complementary to existing work endogenizing men's participation in home production as a function of women's labor market conditions (e.g. Fernández et al., 2004; Feyrer et al., 2008).

1.8 Implications and Empirical Evidence

In this section, I present time trends for career, family, and marriage market outcomes for professional women in a variety of occupation groups from the U.S. Census and the American Community Survey. Cross-sectional variation in these outcomes broadly supports the predictions of my model. While not a causal test of the mechanisms I investigate, it suggests the scope for additional empirical work on their relative importance.

In the data, I focus on two main predictions from Theorem 5. Let a "dual-career" couple be a woman who achieves career and a high-earning or equally-educated husband. The first prediction is that dual-career couples in which the woman has an occupation with costly flexibility are less likely to have children than dual-career couples in which flexibility in the woman's occupation is less expensive. The second, related prediction is that women in occupations with high career costs of family who achieve "career and family" are less likely to be part of a dual-career couple than women in occupations with low career costs of family who achieve career and family.

Estimates from the literature allow me to rank the relative career cost of family for three groups of high-earning occupations. Goldin and Katz (2011) estimate the earnings penalty for spells of non-work for professionals using detailed survey data from Harvard College alumni. They find that individuals with an MD experienced the smallest log earnings penalty for a spell of non-work of given length and MBAs the largest, with individuals with JDs in between.[22] The data were collected in 2006 from select classes graduating between 1969 and 1992. Thus, they can be considered to provide estimates of the family-friendliness of these occupation groups up to the 2000 census.[23]

1.8.1 Data Description

I focus on individuals with post-graduate degrees in three groups of occupations - law, business, and medicine - from the 1980 through 2000 United States Census and the 2010 American Community Survey. These groups are chosen to most closely correspond to the occupation groups for which there are estimates of the cost of flexibility (Goldin and Katz, 2011). I define "law" as reporting an occupation of lawyer or judge, "medicine" as an occupation of physician, optometrist,

[22] Goldin and Katz (2011) find that MDs experienced an earnings penalty of 17.3 log points for a job interruption of 0.1 of years since the bachelor's degree, JDs a penalty of 34.5 log points, and MBAs a penalty of 53.1 log points.

[23] The select sample used in this study may overstate the career cost of family compared to the population in the Census. However, I only use the relative ranking of the occupations in further discussion.

podiatrist, or dentist, and "business" as the managerial and professional specialty occupations.[24] I also include as a comparison group all individuals who have a post-graduate degree but are not in these three categories.[25]

I limit my sample to women between the age of forty and fifty, as women in this age range have most likely completed their child-bearing. A woman has *family* if she reports having at least one of her own children in her home.[26] A woman has *career* if she reports wage and business income equal to at least the twenty-fifth percentile of men working full-time full-year in her profession and in her age group.[27] This is similar to the definition used by Goldin (2006) when analyzing career and family for college graduates. Dual-career couples can either be defined by the husband's education or earnings. In the results reported here, a woman has an *equally-educated spouse* if her husband reports also having a graduate degree. Substantively similar results are obtained if husbands are categorized by earnings.[28] Thus, a *dual-career couple* consists of a woman with career and her equally-educated spouse.

Tables 1.2 and 1.3 and Figure 1.10 provide basic summary statistics and time trends in marriage market outcomes, career, and family for women in business, medicine, and law. All three sets of occupations show a substantial increase in the fraction of women over the course of the sample, with women constituting about a third of each occupation group in 2010. The earnings cutoffs for "career" have remained constant within occupation, with doctors having a

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[24]About 70% of individuals classified as "medicine" are physicians. I exclude from the "business" category legislators, funeral directors, and postmasters and include accountants and auditors, insurance underwriters, other financial specialists, and management analysts. Results are robust to changes in the definition of this group.

[25]Because type of graduate degree is not specified, I am not able to distinguish individuals who once worked in these professions and switched to other occupations or who have been out of the labor force for five or more years. Thus, this residual group may include doctors, lawyers, and businesswomen who no longer practice in their fields.

[26]One potential concern with the selection of this age range is that children may be grown; the time trends documented also hold for women between ages thirty-five and forty-five.

[27]Full-time full-year is defined to be forty or more weeks per year and thirty-five or more hours per week.

[28]The definition of high earning can be with respect to absolute earnings (e.g. if his wage and business income is at least the median of men working full-time, full-year in her occupation and his age group) or with respect to her earnings (e.g. the husband earning some fraction more than his wife).

Table 1.2: Summary Statistics for Professional Women, Ages 40-50, 1980-2010

Occupation Group	1980	1990	2000	2010
Post-BA n.e.c.				
Career	$57,093	$56,297	$52,360	$55,707
Num. Obs.	14,968	54,777	73,963	51,060
Frac. female	0.31	0.45	0.51	0.54
Business				
Career	$75,344	$79,168	$78,540	$88,118
Num. Obs.	1,165	5,346	10,056	9,283
Frac. female	0.11	0.20	0.30	0.33
Law				
Career	$89,058	$89,724	$83,776	$91,157
Num. Obs.	191	1,589	3,683	2,746
Frac. female	0.05	0.15	0.28	0.34
Medicine				
Career	$129,193	$133,706	$128,282	$140,010
Num. Obs.	408	1,326	3,162	2,690
Frac. female	0.06	0.13	0.23	0.32

Source: 1980 - 2000 U.S. Census of Population 5% sample; 2010 American Community Survey 1% sample. The census data are produced and distributed by the IPUMS. Sample is all individuals with a post-college degree. *Medicine* includes all individuals who report an occupation of physician, dentist, ophthalmologist, or podiatrist. *Law* includes all individuals who report an occupation of lawyer of judge. *Business* includes all individuals who report a managerial or professional specialty occupation, excluding funeral directors, litigators, and postmasters, and including accountants and auditors, insurance underwriters, other financial specialists, and management analysts. *Post-BA n.e.c.* includes all individuals with a post-graduate degree not included in law, business, or medicine. *Career* is the 25th percentile business and wage income for men working full-time (35+ hours per week) and full-year (40+ weeks per year) in that profession group and age range in 2010 dollars.

threshold for career about forty percent higher than lawyers or businesswomen. Women in all three professions are substantially more likely to be married in 2010 than in 1980.[29] Doctors are consistently more likely than lawyers and businesswomen to be married and to have children.

1.8.2 Patterns in Career, Family, and Marriage Market Outcomes

The time trends for the percentage of professional women achieving career, family and equally-educated spouse reflect the increased entry and success of women in high-earning professional

[29] *Married* is defined to be married, spouse present. The fraction of professional women *ever married* (married, divorced, windowed, or separated) has remained between eighty and ninety percent for each occupation over the sample.

Table 1.3: Fraction Professional Women Obtaining Career, Family, and Marriage Market Outcomes, Ages 40-50, 1980-2010

	Business				Law			
	1980	1990	2000	2010	1980	1990	2000	2010
Married Women								
Career, Family, and Graduate Spouse	0.05	0.13	0.16	0.17	0.18	0.20	0.25	0.24
Career and Graduate Spouse	0.10	0.19	0.21	0.20	0.25	0.29	0.30	0.28
Family and Graduate Spouse	0.53	0.41	0.37	0.38	0.57	0.53	0.51	0.51
Graduate Spouse	0.68	0.56	0.47	0.45	0.70	0.68	0.61	0.57
Career and Family	0.09	0.21	0.32	0.34	0.24	0.28	0.38	0.41
Career	0.16	0.33	0.45	0.43	0.33	0.41	0.48	0.49
Family	0.75	0.70	0.75	0.81	0.83	0.74	0.80	0.87
Family Given Career and Graduate Spouse	0.55	0.68	0.75	0.83	0.73	0.70	0.82	0.87
Graduate Spouse Given Family and Career	0.62	0.63	0.50	0.48	0.76	0.72	0.65	0.58
Career Given Family and Graduate Spouse	0.10	0.32	0.43	0.44	0.32	0.39	0.48	0.47
All Women								
Career and Family	0.06	0.16	0.23	0.26	0.16	0.20	0.29	0.32
Career	0.19	0.35	0.46	0.43	0.27	0.39	0.49	0.49
Family	0.51	0.53	0.55	0.62	0.61	0.55	0.61	0.67
Married	0.44	0.57	0.57	0.60	0.46	0.56	0.60	0.61
	Medicine				Post-BA n.e.c.			
	1980	1990	2000	2010	1980	1990	2000	2010
Married Women								
Career, Family, and Graduate Spouse	0.25	0.28	0.26	0.25	0.09	0.12	0.12	0.12
Career and Graduate Spouse	0.28	0.33	0.29	0.29	0.13	0.16	0.16	0.14
Family and Graduate Spouse	0.78	0.65	0.62	0.62	0.53	0.40	0.36	0.37
Graduate Spouse	0.86	0.75	0.69	0.68	0.63	0.49	0.43	0.42
Career and Family	0.28	0.35	0.37	0.38	0.15	0.23	0.29	0.30
Career	0.34	0.42	0.42	0.44	0.21	0.31	0.38	0.36
Family	0.87	0.83	0.87	0.89	0.81	0.79	0.80	0.85
Family Given Career and Graduate Spouse	0.89	0.86	0.88	0.88	0.75	0.73	0.78	0.84
Graduate Spouse Given Family and Career	0.89	0.81	0.70	0.66	0.64	0.51	0.42	0.40
Career Given Family and Graduate Spouse	0.32	0.44	0.42	0.41	0.18	0.29	0.34	0.32
All Women								
Career and Family	0.23	0.29	0.30	0.33	0.12	0.19	0.24	0.25
Career	0.36	0.41	0.43	0.45	0.27	0.36	0.42	0.40
Family	0.69	0.69	0.70	0.75	0.60	0.63	0.63	0.69
Married	0.64	0.68	0.68	0.71	0.57	0.64	0.63	0.66

For source, sample, and occupation group definitions, see Table 1.2. *Family* indicates having one or more children in the home. *Career* is business and wage income equal to at least the 25th percentile of men in the same age group working full time full year in that profession. *Graduate spouse* is a husband with a post-graduate degree. *Married* is married, spouse present.

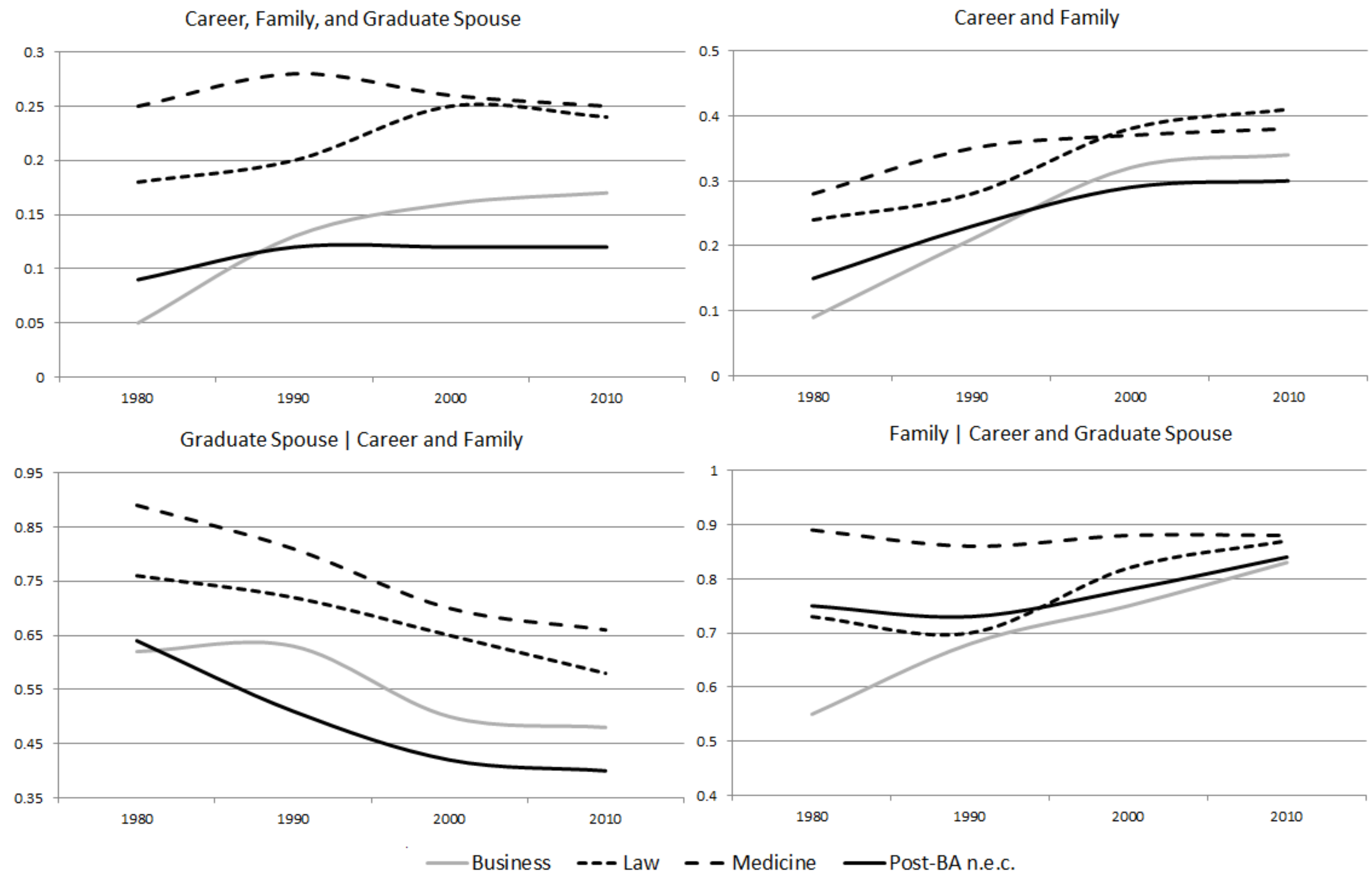

Figure 1.10: Fraction professional married women achieving career, family, and marriage market outcomes, ages 40-50, 1980-2010. Graphs present data from Table 1.3. See Table 1.3 notes for sample information and variable definitons.

fields. Married women in business and law are more likely to achieve career, family, and spouse in 2010 than they were in 1980 (Figure 1.10, Panel 1). In the year 2000, thirty percent of married women in law and medicine achieved all three, with business substantially lower at fifteen percent. A key driver of this trend is an apparent increase in the labor market opportunities of women with children: the probability women have achieved career and family has increased substantially for all three occupations (Figure 1.10, Panel 1).

Panel 4 of Figure 1.10 provides preliminary evidence on one of the main predictions of the model. The probability that a dual-career couple has at least one child varies accross occupations in an ordering consistent with the empirical estimates of flexibility. Throughout the sample period, about ninety percent of dual-career couples including women doctors had at least one child. Dual-career couples including women in law and business were ten to fifteen percentage points less likely to have any children than women in medicine in dual-career couples in 2000; this is a substantial improvement over 1980 when about fifty-five percent of business dual-career couples and seventy-five percent of law dual career couples had any children.[30]

Mitigating the growth of career and family in achieving the triad of career, family and equally-educated spouse, however, is a substantial *decrease* in the probability that the husband of a professional woman who achieves career and family also has a graduate degree (Figure 1.10, Panel 3). This decline is uniform for all four groups of professional women. This increase in women "marrying down" has many potential explanations, including the increasing number of educated women or later ages of marriage (Smits et al., 1999). The cross-sectional variation in these marriage patterns, however, is again consistent with the estimates of flexibility: married women doctors are the most likely to have a graduate spouse and businesswomen are the least, with law in between. Because all three groups have post-graduate degrees, variation in time spent in school is unlikely to explain differences in these marriage patterns, although the nature of the workplace remains a potential confound.

[30] It appears women in business have their children slightly earlier; using the 35-45 age range increases the fertility of dual-career couples where the woman is in business by about ten percentage points. The ordering of professions remains unchanged.

One possible explanation for these cross-occupational patterns is simply income: the income cutoff for career is higher for medicine than for law or business, and this extra income may be used to reduce the career cost of family in dimensions outside the scope of my model. Income, however, does not seem to explain the entirety of the variation in Figure 1.10. While the career cutoff for women in business and law has been approximately equal throughout the sample, women in law have patterns of career, family, and marriage that are closer to doctors than to businesswomen. Women in law are substantially more likely than businesswomen to have an equally-educated spouse conditional on having career and family. Controlling for income in a linear regression model (not reported) does not eliminate this statistically significant difference. Lawyers have also substantially outpaced businesswomen and even surpassed women doctors in the probability of obtaining career and family.

My model provides two potential explanations for the time trends observed in the data. The first is that the increased earning potential of women, combined with changes in social norms and home production technology, have increased the child care participation of professional women's husbands. As discussed in the introduction, this trend has been established for college-educated men in time use data (Aguiar and Hurst, 2007; Guryan et al., 2008). More productive men in the home would result in both more dual career couples with children (if couples share home production) and more professional women marrying lower-earning men (who provide home production). Another potential explanation is that these occupations have experienced a decreased cost of flexibility over time. This seems particularly plausible for the patterns observed in law, in which women now achieve career, family, and spouse at the same rate as medicine, despite earning far less.

1.9 Conclusion

In this paper I have presented an integrated model of occupation choice, spouse choice, labor supply, and fertility. I unify an extensive literature on career and family and provide new testable predictions on the relationships among career, family, and marriage market outcomes. When occupations exhibit high costs of an amenity *flexibility* that impacts the opportunity cost of child care, the equilibrium adjusts on three margins. Fewer women enter these occupations; individuals in these occupations are less likely to marry one another; and high-earning couples in these occupations are less likely to have children. Decreasing the cost of flexibility may simultaneously increase the fraction of women in a high-earning occupation while decreasing their labor supply, as both fertility and positive sorting in the marriage market become more attractive. Introducing occupational amenities changes the incentives for men and women to specialize in home production or market work: when flexibility is costly, the marriage market may reward men and women who are both high-earning and productive in the home. Empirical trends from the Census and the American Community Survey support the predictions of my model.

Reducing this set of complex life choices to the primitives of home production technology and labor market parameters raises fundamental questions about the nature of childcare and of work. Decreasing the cost of flexibility or reducing minimum labor supply requirements can help women to achieve career and family. However, there are occupations - for example as a senior official in the Department of State or the CEO of a major corporation - for which such adjustment may not be possible. The very *nature* of the work prevents its occupant from engaging in non-trivial amounts of home production. For women achieve "career and family" in such positions may thus require adjustment of the dynamics of and preferences in the marriage market.

Chapter 2

Spouse Choice and Female Labor Supply: Evidence from Lawyers

2.1 Introduction

The literature on the relationship between marriage market outcomes and the occupation choices, educational investments, and labor supply of women has seen a recent resurgence. In parallel with recent media and academic attention on the lack of women in high-powered professional roles (see e.g. Bertrand and Hallock (2001)), a growing literature has investigated the relationship between the nature of work in different occupations and tradeoffs between marriage, career, and family (Bertrand et al., 2010; Goldin and Katz, 2011, 2012). This literature has advanced the importance of occupational amenities as well as wages in the choice of occupation for mothers and the career cost of having a family. It builds on a literature documenting the willingness of women to purchase flexibility in work hours (Altonji and Paxson, 1992) as well as incorporating the importance of household bargaining in determining female labor supply (Chiappori, 1992; Chiappori et al., 2002; Blundell et al., 2005, 2007).

In this paper I empirically investigate the relationship between spouse choice and the family and labor supply decisions of highly-educated professional women. Previous work has shown that

that highly-educated professionals have a propensity to marry others in the same profession due to both preferences for similar mates and search frictions (Kalmijn, 1994; Lee, 2011). With time demands at work increasing among highly-educated salaried workers (Kuhn and Lozano, 2008), dual-career professional couples with children may face increasing time conflicts at home from competing job demands. This acute career and family conflict is one of many hypotheses for why professional organizations have struggled to retain qualified women in mid- and upper-level positions, despite their growing presence in the lower ranks (Harvard, 2005; Catalyst, 2010). Recent research has begun to investigate the importance of spouse characteristics for the labor supply decisions of professional mothers: MBAs with children and high-earning husbands are more likely to reduce their weekly hours and take career breaks, thus incurring steep career penalties (Bertrand et al., 2010).

I build on this line of work by examining the implications of sorting in the marriage market for the labor supply and fertility decisions for high-powered professional women. If higher-ability women are more likely to marry higher-earning men even within the population of elite professionals, then the time challenges of dual-career couples with children will fall most acutely on those women with the highest potential to rise to the top of their fields. Having high-earning husbands also gives these women the unique freedom to take breaks from work, exchanging income for more time with family at critical stages of childhood. Thus, assortative mating may have real implications for which set of professional women opt in and out of the labor force and the fraction of women in top professional positions.

I investigate these dynamics using the University of Michigan Law School Alumni Survey, a longitudinal administrative survey with detailed information on school performance, work history, children and childcare, spouse characteristics, and family and career satisfaction. The portion of the survey I use spans almost 20 years, administered from 1987 to 2006, and covers 30 years of law school graduates. Attendees of this law school are an accomplished group, with 12% coming from Ivy League or Seven Sisters colleges and a median LSAT national percentile of 95. This group provides an excellent case study of the labor supply patterns above: over the course of the survey period the fraction of women in the law school class grew from 5% in 1970 to 46% in 2000 (Figure 2.1) while the fraction of women working full-time 15 years after law school graduation dropped from 86% in the class of 1970 to 63% in the class of 1990 (Figure 2.2).

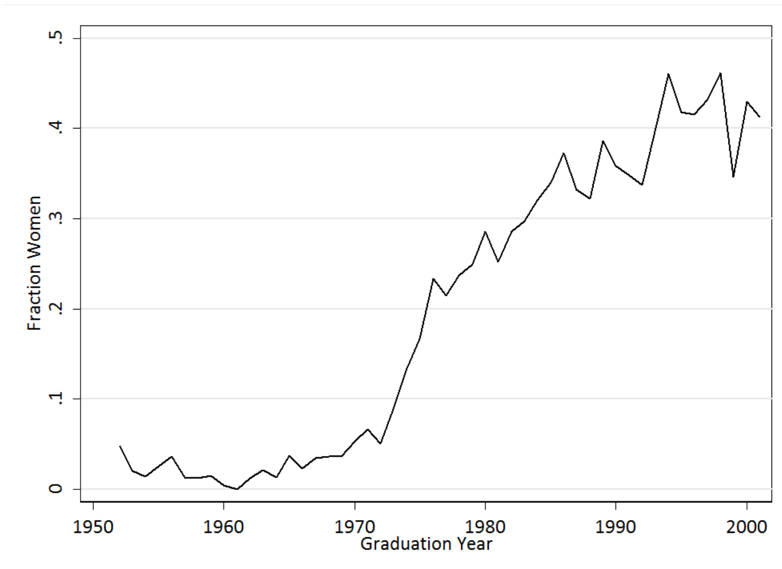

Figure 2.1: The fraction of each graduating class who are female. Sample includes all students who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

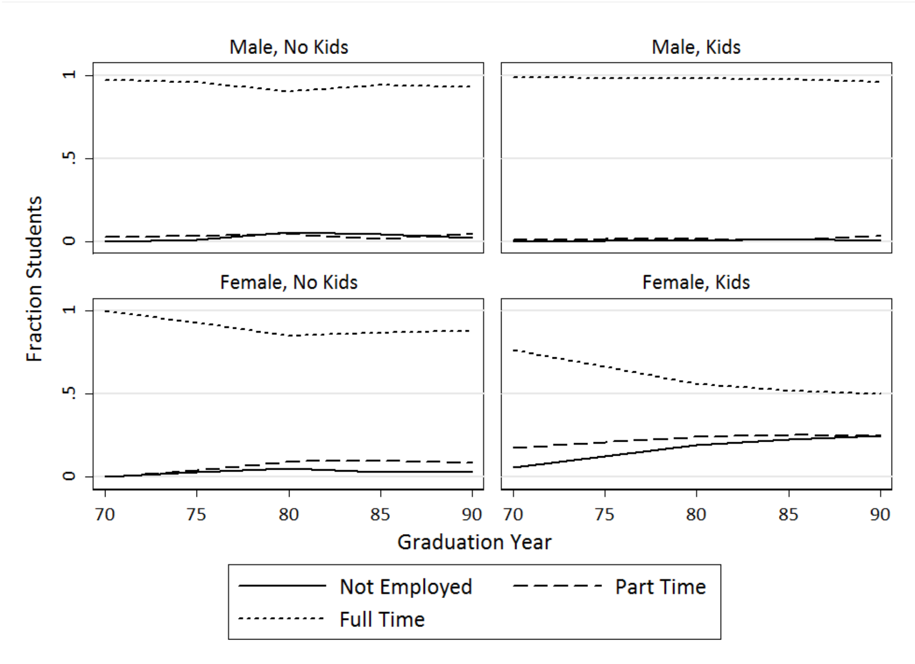

Figure 2.2: Labor supply outcomes 15 years after graduation by graduation year, gender, and whether respondent has children. Sample includes all survey respondents who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

I first provide a decomposition of the gender earnings gap for lawyers, updating the study of Wood et al. (1993). At five and 15 years after graduation, female survey respondents have earnings that are 11 and 53 log points lower, respectively, than their male counterparts. Using the first three years of survey data taken 15 years after graduation, Wood et al. (1993) find that controlling for demographics, performance, labor force participation, and job characteristics still leaves one-fourth to one-third of the gender gap in earnings unexplained. I find that at five years after graduation, the entire gender gap in earnings can be explained by gender differences in law school performance and current and prior labor supply. At 15 years, controlling for workplace setting as well renders the unexplained earnings differential between men and women statistically insignificant. A key component of the gender gap in earnings in the 15-year survey seems to be that men lawyers are more likely to enter highly lucrative non-law jobs in business and finance. These findings echo the results of Bertrand et al. (2010), who find that differences in human capital investments and past and current labor supply can explain 83% of the gender gap in earnings among MBAs 12 years after graduation from business school.

I then assess changes in the career cost of family across time at five and 15 years after graduation. I find evidence of an increase in "linearity" in the career cost of family with respect to time out of the labor force 15 years after graduation. While women graduating in the first half of the sample experience a large, discrete earnings penalty for having spent six or more months out of the labor force, women in the second half of the sample experience an earnings penalty proportional to the number of months spent not working. This results in a lower earnings penalty for graduates with spells of non-work less than two years long. While the workplace settings of workers with prior spells of non-work have not changed over the 20 years of the survey, there is some evidence that large law firms and corporate settings are increasingly allowing reductions in labor supply in the form of part-time work. The relationship between changes in job design in corporate law settings in the decrease in the career cost of family is a topic that deserves futher exploration.

In the second section of the paper, I address the relationship between positive assortative mating on earnings and the labor supply and fertility decisions of high-ability female lawyers. Because the gender gap in earnings can largely be explained by observables, I can predict the earnings potential of the women had they pursued careers "like men," without reductions in labor supply for spouse and family. I find that women with higher earnings potential are more likely to be married five years after graduation, and by 15 years after graduation, there is a strong positive correlation between a woman's earnings potential and the earnings of her husband. Moreover, spousal earnings have first-order effects on women's fertility and labor supply: mothers with high-earning husbands are less likely to be in the labor force and work fewer hours conditional on working than mothers with lower-earning husbands. They also have more children, which is correlated with reduced labor supply. Thus, the women with the highest earnings potential are those who are most likely to be opting out due to the pressures of career and family. Moreover, these correlations only hold for the second half of the sample, when the earnings penalty for modest spells of non-work decreased. I therefore argue that the decrease in the earnings penalty for spells of non-work resulted in a decrease in labor supply for women with the highest earnings potential, as these women have the spousal resources to take advantage of the reduced cost of this amenity.

The empirical results here can best be understood in the frameworks of Becker (1973) and in Chapter 1. Becker first observed that negative assortative mating on labor market skill is socially efficient with respect to maximizing the labor force participation of the highest-ability individuals, especially if there are increasing returns to scale for labor market or home work. Here, as in his treatise, positive assortative mating is instead pervasive. The framework in Chapter 1 provides an explanation: if child care cannot be efficiently shifted from wives to husbands, then positive assortative mating on earnings potential is the unique marriage market equilibrium. Moreover, if women have an advantage in child care, a decrease in the discrete earnings penalty from reduced labor supply will result in high-earning couples shifting childcare from the husband to the wife and a reduction in the wife's labor supply. This decrease in constraints, however, makes entering a high-earning occupation (or a high-earning track within an occupation) more attractive for women, as it allows them to "have it all": a high-earning spouse, family, and stimulating work with flexibility in labor supply.

2.2 The Data

The University of Michigan Law School (UMLS) Alumni Survey is an annual several-hundred question survey administered by the law school for administrative purposes. Graduates are contacted 5, 15, 25, 35, and 45 years after graduation and asked detailed questions about work history, family, current jobs, time use, and career and life satisfaction. These responses are matched to administrative data that includes application information, law school performance, and demographics. The survey has been administered every year from 1967 through 2006. I restrict the data to survey years in which questions on spouse income and occupation, own labor supply history, and undergraduate performance were asked (5-year: 1982-2000; 15-year:1972-1991).

UMLS is consistently ranked among the top 14 law schools in the country. For the years for which there is 15-year survey data, UMLS was particularly prestigious: US News and World Report's inaugural ranking of law schools in 1987 ranked UMLS third in the country, behind only Yale and Harvard (Lomio et al., 2008). Throughout our sample period, the median student had an LSAT score at least at the 90th percentile among all LSAT takers nationally (Figure 2.3). About 12% of students attended Ivy League or Seven Sisters schools as undergraduates (Table 2.1).

Figure 2.3: LSAT national percentile distribution by gender and graduation year. Sample includes all students who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

The demographics of the student body have evolved in line with broader changes in professional school attendance. From 1970 to 2000 the fraction of women has increased from just under 10% to approximately 40% (Figure 2.1). This is similar to the trends documented for a broader sample of lawyers by Goldin and Katz (2011). The student body is also more racially diverse: the fraction African American graduates increased in the 1970's and remained at slightly below 10% throughout the sample, and the fractions Hispanic and Asian students have steadily increased over the last three decades (Table 2.1). Mean age at graduation for both men and women has remained constant at about 26 years old (Table 2.1). The substantial year-to-year fluctuation in mean age of graduation may reflect changes in economic conditions and outside employment opportunities (Figure 2.4).

Figure 2.4: Mean age at graduation by gender. Sample includes all students who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

I exclude from the subsequent analysis individuals who graduated after age 30. While an interesting sub-group, these individuals face different career and family tradeoffs than those who graduate during the "typical" ages of 25-27. Specifically, they are more likely to have resolved career and family negotiations before deciding to attend law school. This eliminates about 10% of the sample. In addition, I exclude anyone who took more than five years to finish law school (<1% of respondents). This leaves a sample of 4,125 respondents to the fifth-year survey and 4,233 for the 15th.

Table 2.1: Baseline Summary Statistics

	1972-1980		1981-1990		1991-2000	
	Men	Women	Men	Women	Men	Women
Academic						
Mean Law School GPA	0.061	-0.153	0.055	-0.104	0.089	-0.11
	(0.983)	(0.958)	(0.984)	(0.974)	(0.996)	(0.972)
Mean LSAT Percentile	88.5	85.7	90.0	88.0	85.9	84.7
	(14.6)	(18.2)	(13.3)	(14.6)	(23.6)	(23.2)
Fraction Ivy League	0.13	0.13	0.12	0.13	0.12	0.14
or Seven Sisters	(0.34)	(0.33)	(0.33)	(0.34)	(0.33)	(0.35)
Fraction Transfer	0.03	0.06	0.03	0.03	0.08	0.07
	(0.18)	(0.24)	(0.17)	(0.18)	(0.27)	(0.26)
Mean Undergraduate	0.04	0.12	0.08	0.03	0.03	0.04
GPA	(0.96)	(0.92)	(0.92)	(0.98)	(0.97)	(0.98)
Demographic						
Fraction African American	0.06	0.13	0.05	0.10	0.07	0.11
	(0.23)	(0.33)	(0.21)	(0.30)	(0.26)	(0.32)
Fraction Hispanic	0.008	0.01	0.04	0.03	0.06	0.04
	(0.09)	(0.11)	(0.20)	(0.17)	(0.23)	(0.20)
Fraction Asian	0.003	0.009	0.01	0.02	0.04	0.07
	(0.05)	(0.09)	(0.12)	(0.15)	(0.20)	(0.26)
Mean Age at Graduation	25.8	25.7	25.9	25.9	26.1	26.0
	(1.49)	(1.58)	(1.40)	(1.50)	(1.51)	(1.54)
Observations	3120	576	2339	1061	1961	1362

Sample includes all students who graduated before age 31 and in less than six years. Standard deviations included in parentheses. See Appendix B for variable definitions.

2.3 Survey Non-Response

Average response rates for the survey are high (5-year: 68%; 15-year: 67%) but have declined steadily over time (Figure 2.5). T-tests for differences in means (not reported) show that non-respondents had systematically worse law school performance than respondents. To control for this non-randomness in survey response, I model the response probability using a probit model with covariates drawn from performance measures and demographics from UMLS's administrative records. The probability that person i with observables X_i responds to the survey is

$$r_i = \Phi(X_i'\beta)$$

where X_i includes gender and race; undergraduate grade point average (GPA) and institution type; law school GPA, LSAT national percentile, and whether a transfer; and dummies for graduation year in five-year groups.

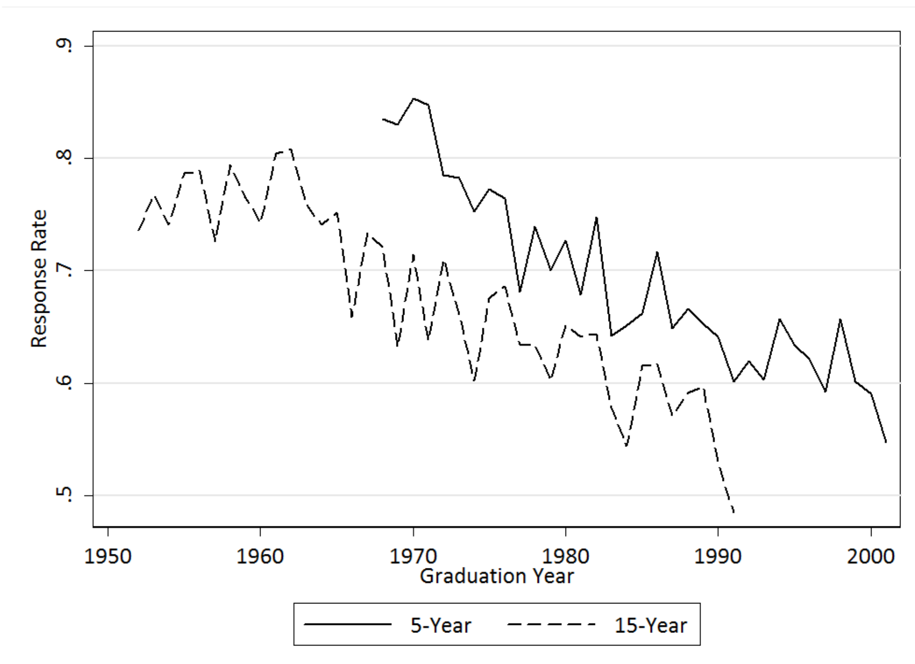

Figure 2.5: Probability of survey response by graduation year. Sample includes all students who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

The regression results confirm that individuals with better law school performance are more likely to respond to the survey (Table 2.2). Law school GPA has a positive and highly significant effect on the probability of response. Women are more likely than men to answer the 5-year survey. Undergraduate institution and other performance measures have no predictive power, except that Ivy League / Seven Sisters graduates are less likely to respond (not reported). The predicted probabilities of response $\hat{r}_i$ are bounded away from zero with a smooth, single-peaked distribution (see Figure 2.6).

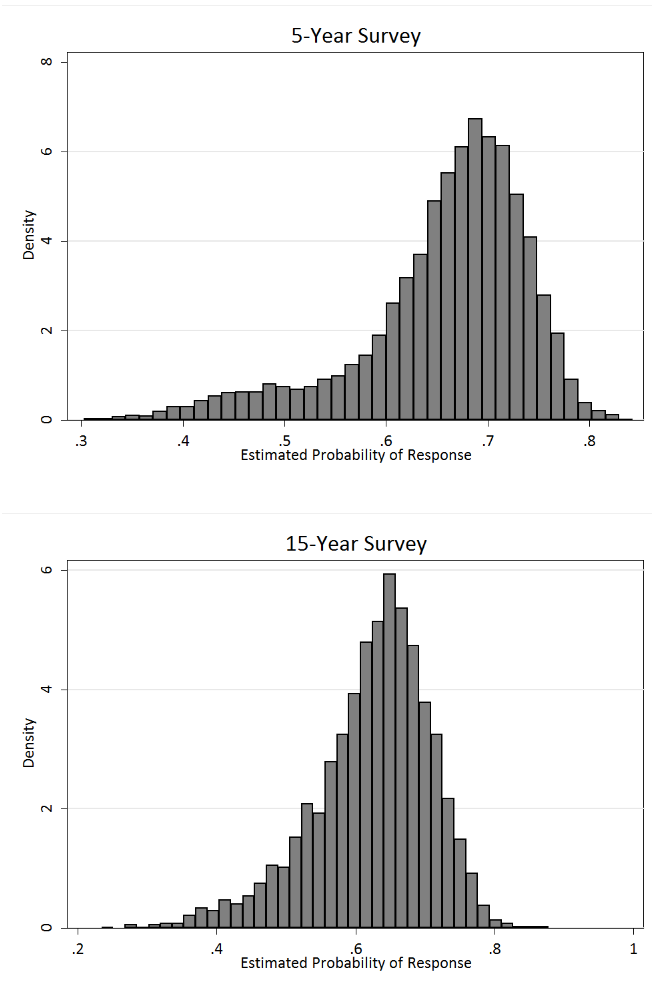

Figure 2.6: Estimated probability of survey response using administrative data. Estimates calculated using regressions 1 (5th year) and 4 (15th year) from Table 2.2 for all students graduating before age 31 and in less than six years.

I weight each observation by the inverse of the estimated probability of non-response $\hat{r}_i$ from the pooled regressions (Table 2.2, Columns 1 and 4). This is a standard method in the survey data

Table 2.2: Probability of Survey Response

	(1) 5th Year	(2) 5th Year, Women	(3) 5th Year, Men	(4) 15th Year	(5) 15th Year, Women	(6) 15th Year, Men
Female	0.11***			0.04		
	(0.03)			(0.04)		
Law School GPA	0.14***	0.14***	0.14***	0.15***	0.18***	0.14***
	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)
LSAT Percentile	0.00**	0.01	0.00	0.00	0.01**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Transfer	-0.11	-0.09	-0.14	-0.05	0.04	-0.09
Student	(0.09)	(0.15)	(0.11)	(0.09)	(0.17)	(0.11)
Undergraduate	-0.01	0.01	-0.02	-0.03	0.01	-0.04*
GPA	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)
Constant	-2.57	-7.02	0.55	-1.30	3.68	-2.88
	(4.35)	(6.71)	(5.76)	(3.91)	(7.37)	(4.65)
Age, Age Squared.	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6380	2339	4041	6821	1710	5110
Pseudo R^2	0.025	0.033	0.022	0.022	0.033	0.023

Probit regressions with dependent variable equal to 1 if graduate responded to survey. Significant at: * 10%; ** 5%; *** 1%. Sample includes all students in the classes of 1982-2000 (5th year) and 1972-1991 (15th year) who graduated before age 31 and in less than six years. Dummy variables for missing values of independent variables included but not reported. See Appendix B for variable definitions.

literature for reducing the bias from non-random survey non-response (see e.g. Little (1986)). I opt for reweighting rather than a control function approach because the administrative variables do not contain an observable that can be used as an instrument for response. The regression results I report in the rest of the paper do not correct for the uncertainty from estimating the response weights.

2.4 The Gender Earnings Gap

Since the work of Wood et al. (1993), another 15 years of survey data from the UMLS has been collected. The larger panel allows me to measure how the career cost of family has changed over time as well as how it differs across different law and non-law-practice settings.

2.4.1 Patterns in Earnings, Hours, and Labor Supply Over Time

Table 2.3 provides summary statistics for earnings and labor supply for individuals who are in the work force at the time of the survey. Michigan graduates are generally a high-paid group: the median first year graduate's earnings have grown from about $69,000 in the 1970's to $88,000 in the 1990's, and at 15 years after gaduation the median man earned from between $189,000 in the 1970's to $234,000 in the 1990's. Mean and median weekly hours for men have remained relatively steady over the sample. The average woman reports spending over a year working part-time and over a year not working, while men report almost no labor supply reductions (Table 2.4)

Two patterns are worth noting in Tables 2.3 and 2.4. The first is the growth in earnings inequality even among this group of highly-educated lawyers. The standard deviation of earnings for men 15 years after graduation has almost quadrupled over the three decades of the survey, from $174,000 to $731,000. A more modest increase is evident in the five year surveys. The second pattern of interest is the systematic decrease in labor supply for female graduates 15 years after graduation over these three decades. Between the first and second decade of the sample,

Table 2.3: Employment Summary Statistics for Respondents in Labor Force

	1972-1980		1981-1990		1991-2000	
	Men	Women	Men	Women	Men	Women
1st Year						
Mean Earnings	68,265	66,239	78,752	77,716	88,306	84,545
Median Earnings	65,365	62,984	75,657	75,657	88,522	83,953
Standard Deviation Earnings	25,788	23,755	27,538	27,496	36,983	37,055
Fraction Govt. / Pub. Serv.	0.18	0.26	0.08	0.12	0.10	0.14
Observations	2352	446	1,800	800	1,168	877
5th Year						
Mean Earnings			109,373	98,110	130,765	115,714
Median Earnings			105,139	95,165	116,243	105,698
Standard Deviation Earnings			46,798	41,816	79,533	69,923
Mean Weekly Hours			53	50	53	51
Median Weekly Hours			50	50	53	51
Standard Deviation Weekly Hours			9.1	10.1	10.5	10.8
Observations			1,305	570	1,079	761
15th Year						
Mean Earnings	231,377	147,449	270,151	167,661	406,411	149,413
Median Earnings	189,142	121,941	194,815	126,402	233,518	106,144
Standard Deviation Earnings	172,710	128,365	294,375	157,816	731,435	150,472
Mean Weekly Hours	51	44	50	41	51	40
Median Weekly Hours	50	45	50	45	50	41
Standard Deviation Weekly Hours	8.3	12	9.0	14	10.5	13
Observations	1,567	287	1,198	455	91	46

All income in 2007 dollars. Sample includes all survey respondents from the classes of 1982-2000 (5th year) and 1972-1991 (15th year) who completed law school in no more than six years and graduated before the age of 31. See Appendix B for variable definitions. Earnings and labor supply data only available for individuals currently in the labor force.

Table 2.4: Labor Supply Summary Statistics

	1972-1980		1981-1990		1991-2000	
	Men	Women	Men	Women	Men	Women
5th Year						
Fraction Part-Time			0.02	0.05	0.02	0.04
Fraction Not Working			0.01	0.06	0.02	0.07
Fraction Ever Part-Time			0.04	0.14	0.07	0.15
Fraction Ever Not Working			0.05	0.26	0.08	0.22
Mean Years Part-Time			0.05	0.21	0.06	0.11
Mean Years Not Employed			0.06	0.25	0.05	0.15
Mean Years Practicing Law			3.81	3.43	3.49	3.18
Observations			1,408	647	1,174	881
15th Year						
Fraction Part-Time	0.01	0.16	0.02	0.24	0.03	0.24
Fraction Not Working	0.00	0.08	0.02	0.18	0.00	0.18
Fraction Ever Part -Time	0.04	0.38	0.09	0.45	0.14	0.41
Fraction Ever Not Working	0.04	0.38	0.10	0.44	0.09	0.31
Mean Years Part-Time	0.10	1.29	0.14	1.56	0.23	1.60
Mean Years Not Employed	0.08	1.00	0.14	1.34	0.13	1.29
Mean Years Practicing Law	10.22	7.25	9.57	7.55	9.48	7.25
Observations	1,712	345	1,358	628	106	63

Sample includes all survey respondents from the classes of 1982-2000 (5th year) and 1972-1991 (15th year) who completed law school in no more than six years and graduated before the age of 31. See Appendix B for variable definitions.

the median hours, median earnings, and average time in the labor force for women graduates decreased. The median woman in the work force 15 years after graduation works ten hours less than the median man in the most recent set of 15-year surveys.

2.4.2 Defining Labor Supply and Workplace Setting

Survey respondents provide both the hours per week and weeks per year worked in the previous year. In addition, they report the number of years since graduation spent working part-time, years spent out of the labor force, and years spent practicing law. I define an individual to have positive current labor supply if he or she reports working more than zero hours per week and more than zero weeks per year. If both of these variables are missing, an individual is not currently working if he or she reports being not employed at the current time. I decompose past labor supply in to two parts: indicators for whether the individual reports ever working part time or ever being out of the labor force for more than six months, and linear terms for years spent working part time, years spent out of the labor force, and years spent practicing law. This decomposition allows me to measure both the linear and discrete cost of time off as in Goldin and Katz (2011).

A respondent's current job is categorized by function and setting. Following the coding of the UMLS survey team, I summarize each workplace as one of law firm, corporate counsel, government / legal services / public interest, or not practicing. Non-practice settings include teaching, business, and the judiciary. Attorneys in law firms are classified as solo practicioners, partners, associates, or "other" (including of counsel).

Among individuals whom I classify as in the labor force, 96% have current earnings data in the 5 year survey and 92% in the 15-year. There is no evidence that the observations missing earnings are systematically different than those with responses, so I consider these observations to be missing at random. Observations with missing job description or labor supply variables are coded with a dummy and included in the sample.

2.4.3 Gender Earnings Gap Across Career Stages and Workplace Settings

Following the literature, I estimate a series of earnings equations that measure the difference in mean earnings between men and women conditional on observables. The coefficient on female measures the difference in mean earnings between men and women that cannot be explained by the observables included in the regression. The regressions have the form

$$y_i = \beta_0 + \beta_1 \cdot female_i + \beta_2 \cdot X_i + d_{jdyr} + \epsilon_i$$

where y_i is log earnings from employment in the year of the survey, X_i are individual characteristics, d_{jdyr} are graduation-year dummies, and ϵ_i is an iid error. For each of the fifth year and 15th year survey, I allow X_i to include baseline controls (law school and undergraduate performance, demographics, and current location), current labor supply, past labor supply, and workplace characteristics.

A first-order concern is that an analysis of working individuals will fail to reveal discrimination if women who believe their future earnings are low due in part to discrimination opt out of the labor force. Patterns of fertility and marriage indicate that women with reduced labor supply are mothers with relatively high law school performance and high-earning spouses. I model selection in to the labor force in the next section.

Tables 2.5 and 2.6 present, respectively, earnings regressions for respondents five and 15 years after graduation. Among lawyers with positive labor supply, and without including any controls, women report earnings that are 11 log points lower than their male counterparts five years after graduation (significant at 1%) and a staggering 54 log points 15 years after graduation (also significant at 1%).

Table 2.5: Gender Gap in Earnings Among the Employed, 5th Year Survey

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.11***	-0.11***	-0.09***	-0.05***	-0.01	-0.00	0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Law School GPA			0.15***	0.13***	0.12***	0.12***	0.12***
			(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
LSAT Percentile			-0.00	-0.00	-0.00	-0.00	-0.00
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Undergraduate			-0.02**	-0.02*	-0.02*	-0.02*	-0.02*
GPA			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log Hrs/Week				0.50**	0.46***	0.42**	0.40**
				(0.16)	(0.14)	(0.15)	(0.15)
Log Hrs/Week x				0.07*	0.00	0.01	0.01
35-50 Hrs/Wk				(0.03)	(0.03)	(0.03)	(0.03)
Log Hrs/Week x				0.07*	-0.00	0.01	0.01
50-65 Hrs/Wk				(0.03)	(0.04)	(0.04)	(0.04)
Log Hrs/Week x				0.05	-0.01	-0.00	-0.00
>65 Hrs/Wk				(0.04)	(0.04)	(0.05)	(0.05)
Log Weeks/Yr				0.49***	0.32***	0.34***	0.32***
				(0.11)	(0.07)	(0.07)	(0.06)
Ever Part-Time					-0.09***	-0.08***	-0.07***
					(0.02)	(0.02)	(0.02)
Ever Not Emp.					-0.08**	-0.10**	-0.09**
					(0.03)	(0.03)	(0.03)
Years Part-Time					-0.20***	-0.21***	-0.20***
					(0.03)	(0.03)	(0.02)
Years Not Emp.					-0.21**	-0.22**	-0.22***
					(0.07)	(0.07)	(0.06)
Years Prac. Law					0.09***	0.06***	0.06***
					(0.01)	(0.01)	(0.01)
Constant	11.57***	12.98***	12.66***	8.48***	8.04***	7.28***	6.87**
	(0.04)	(2.34)	(2.34)	(2.04)	(1.71)	(2.10)	(2.17)
Age, Age Squared	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	Yes	Yes	Yes	Yes	Yes
Workplace Setting	No	No	No	No	No	Yes	Yes
Non-Practice Setting	No	No	No	No	No	No	Yes
Observations	3702	3702	3702	3702	3702	3702	3702
R^2	0.052	0.184	0.235	0.348	0.465	0.491	0.508

Outcome is log annual earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Sample includes all survey respondents from the classes of 1982-2000 currently in the labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values and whether transfer student included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Table 2.6: Gender Gap in Earnings Among the Employed, 15th Year Survey

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.54***	-0.51***	-0.50***	-0.21***	-0.07**	-0.07***	-0.06**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Law School GPA			0.16***	0.15***	0.12***	0.12***	0.12***
			(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
LSAT Percentile			-0.01***	-0.01***	-0.00***	-0.00***	-0.00***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Undergraduate			-0.02	-0.01	-0.00	-0.00	-0.00
GPA			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log Hrs/Week				0.97***	1.00***	0.99***	0.96***
				(0.14)	(0.12)	(0.12)	(0.11)
Log Hrs/Week x				0.05	-0.05	-0.05	-0.04
35-50 Hrs/Wk				(0.04)	(0.03)	(0.03)	(0.03)
Log Hrs/Week x				0.08*	-0.04	-0.04	-0.04
50-65 Hrs/Wk				(0.04)	(0.03)	(0.03)	(0.03)
Log Hrs/Week x				0.02	-0.09**	-0.09**	-0.08**
>65 Hrs/Wk				(0.03)	(0.03)	(0.03)	(0.03)
Log Weeks/Yr				0.57**	0.41*	0.43*	0.42*
				(0.21)	(0.19)	(0.20)	(0.20)
Ever Part-Time					-0.24***	-0.24***	-0.20***
					(0.06)	(0.06)	(0.05)
Ever Not Emp.					-0.09**	-0.08*	-0.07*
					(0.03)	(0.04)	(0.03)
Years Part-Time					-0.04***	-0.04***	-0.04***
					(0.01)	(0.01)	(0.01)
Years Not Emp.					-0.09***	-0.10***	-0.09***
					(0.02)	(0.02)	(0.02)
Years Prac. Law					0.03***	0.02***	0.02***
					(0.00)	(0.00)	(0.00)
Constant	12.16***	11.34*	13.00*	2.98	3.04	1.23	3.23
	(0.04)	(5.88)	(5.86)	(5.59)	(4.42)	(3.91)	(3.87)
Age, Age Squared	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	Yes	Yes	Yes	Yes	Yes
Workplace Setting	No	No	No	No	No	Yes	Yes
Non-Practice Setting	No	No	No	No	No	No	Yes
Observations	3631	3631	3631	3631	3631	3631	3631
R^2	0.083	0.196	0.230	0.412	0.474	0.494	0.516

Outcome is log annual earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Sample includes all survey respondents from the classes of 1972-1991 currently in the labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values and whether transfer student included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

In both the five and 15 year survey, the combination of current and past labor supply, aptitude measures, and workplace setting can explain virtually all of the gender gap in earnings. When all controls are included, the coefficient on female at five years is actually positive, though not different from zero, while a statistically significant earnings gap of 7.6 log points (14% of the raw gap) remains in the 15th year. This residual gender gap for 15 years is strikingly close to that found by Wood et al. (1993) even though they only consider three years of data.[1]

In Table 2.7 I investigate the unexplained portion of the 15-year earnings gap by estimating earnings equations for each of the four workplace settings. For the three law practice settings (law firms, corporate counsel, and government / legal services / public interest), the gender gap in earnings is almost entirely eliminated when controls for school performance and labor supply are included. The unexplained residual gap remains only for non-practicing lawyers. Replacing controls for workplace setting with more detailed controls for organization type cuts the magnitude of the gender earnings gap in half and it is no longer statistically significantly different from zero (Column 5). The coefficients on organization type (not reported) suggest that the residual earnings difference is due to men lawyers having a higher propensity to take high-paying non-law business and finance jobs.

[1] Wood et al. (1993) also include marital status and number of children as controls in their earnings regressions. I instead include these as controls and only include work-related controls in my earnings equations. They also do not decompose the earnings penalty from time off in to discrete and continuous parts.

Table 2.7: Gender Gap in Earnings Among the Employed by Work Setting, 15th Year Survey

	(1) Law Firm	(2) Corporate	(3) Govt/Pub Serv	(4) Non-Practicing	(5) Non-Practicing
Female	-0.04	0.03	-0.04	-0.14	-0.06
	(0.04)	(0.05)	(0.03)	(0.08)	(0.07)
Log Hrs/Week	1.06***	1.09***	0.17	0.92***	0.82***
	(0.15)	(0.18)	(0.37)	(0.12)	(0.12)
Log Hrs/Week x	-0.00	-0.07	0.01	-0.08*	-0.06
35-50 Hrs/Wk	(0.04)	(0.08)	(0.04)	(0.04)	(0.04)
Log Hrs/Week x	-0.00	-0.07	0.03	-0.02	-0.01
50-65 Hrs/Wk	(0.04)	(0.08)	(0.05)	(0.05)	(0.05)
Log Hrs/Week x	-0.06	-0.12	-0.03	-0.08	-0.05
>65 Hrs/Wk	(0.03)	(0.07)	(0.06)	(0.07)	(0.09)
Log Weeks/Yr	-0.03	0.83***	0.55	0.38	0.32
	(0.14)	(0.15)	(0.37)	(0.30)	(0.24)
Ever Part-Time	-0.16**	-0.07	-0.12	-0.41***	-0.28**
	(0.07)	(0.11)	(0.08)	(0.12)	(0.09)
Ever Not Emp.	-0.17***	-0.24***	-0.04	-0.02	0.03
	(0.05)	(0.05)	(0.04)	(0.12)	(0.10)
Years Part-Time	-0.02	-0.02	-0.03	-0.07**	-0.07***
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
Years Not Emp.	-0.07***	0.05	-0.01	-0.10**	-0.10*
	(0.02)	(0.04)	(0.02)	(0.04)	(0.04)
Years Prac. Law	0.04***	0.00	0.00	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Constant	2.45	-2.11	-3.16	-15.37	0.84
	(4.28)	(9.68)	(9.38)	(10.32)	(12.30)
Age, Age Squared	Yes	Yes	Yes	Yes	Yes
Race Dummies	Yes	Yes	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes	Yes	Yes
Undergraduate Controls	Yes	Yes	Yes	Yes	Yes
Law School Controls	Yes	Yes	Yes	Yes	Yes
Organization Type	No	No	No	No	Yes
Observations	2039	470	376	681	681
R^2	0.485	0.401	0.440	0.496	0.565

Outcome is log annual earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Sample includes all survey respondents from the classes of 1972-1991 currently in the labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values and whether transfer student included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Following Wood et al. (1993) and Bertrand et al. (2010), I decompose the gender earnings gap for each year in to its component parts in Table 2.8. The contribution of a set of variables to explaining the gender earnings gap is measured as $\sum_v \beta_v(\bar{X_m} - \bar{X_f})$, where v index the variables in that group (for example, demographics), β_v is the coefficient on each v from the preferred regression, and $\bar{X_{v,m}} - \bar{X_{v,f}}$ is the difference in means between men and women for variable v in the data. For both survey years my preferred regression includes baseline performance and current and past labor supply but not workplace characteristics (Regression 4 in Tables 2.5 and 2.6).

Past labor supply is by a huge margin the largest explanatory set of variable for the gender gap in earnings in both the fifth and 15th year surveys. Previous spells of part-time and non-work explain 49% of the gender earnings gap five years after graduation and 43% 15 years after. Current labor supply is the second-most important set of explanatory variables, and are far more important at 15 years than at five (34% compared to 17%). Unsurprisingly, academic performance is more important at five years (15%) than at 15, at which point it is almost irrelevant.

From the point of view of discrimination, this decomposition is encouraging and mirrors the conclusions in Bertrand et al. (2010). For at least the first five years of a career, earnings are entirely a function of school performance and labor force participation. Controlling for job choice - an outcome which may be an endogenous outcome of discrimination or family time constraints - is not required to eliminate the gender earnings gap. 15 years after graduation, these same choice variables can entirely account for earnings differences between men and women who practice law and 86% of the gap overall, although selection in to workplace setting plays an important role, in particular for non-practicing lawyers.

2.4.4 Linearity of the Gender Earnings Gap and Changes Over Time

An important component of the family-friendliness of a high-earning occupation is the discreteness of the earnings penalty as a function of time away from work (Goldin and Katz, 2011). Occupations that impose a large discrete penalty in earnings for any nontrivial reduction in la-

Table 2.8: Gender Gap in Earnings Decomposition

	5th Year		15th Year	
		% Raw Gap		% Raw Gap
Raw Gender Gap	-0.11		-0.54	
Residual Gap	-0.011	0.10	-0.080	0.15
Gap Explained by				
Demographics	0.002	-0.02	-0.017	0.03
Academic Performance	-0.017	0.15	-0.011	0.02
Current Labor Supply	-0.019	0.17	-0.186	0.34
Past labor supply	-0.054	0.49	-0.233	0.43

Calculations based on Regression 5 from Tables 2.5 and 2.6. Dependent variable is log earnings in 2007 dollars. Sample includes all respondents from the classes of 1982-2000 (5th year) and 1972-1991 (15th year) currently in the labor force who completed law school in no more than six years and graduated before the age of 31. Demographics include race, gender, age, and current location. Academic performance includes law school GPA, LSAT percentile, undergraduate GPA, and undergraduate school. Current labor supply includes current hours per week and weeks per year. Past labor supply includes years worked part-time, years out of labor force, and years practicing law. See Appendix B for variable definitions and text for decomposition methodology.

bor supply are particularly family-unfriendly as workers may never recover from a short period of absence. Moreover, this steep drop in earnings may discourage them from trying to do so. The regressions in Tables 2.9 and 2.10 shed light on the (non-)linearity of the cost of time off for three dimensions of reduced labor supply. For each survey wave I report a pooled regression where labor supply terms are interacted with decade and separate regressions by decade.

Table 2.9: Changes in Career Cost of Family Over Time, 5th Year Survey

	(1) All	(2) 1982-1990	(3) 1991-2000
Female	0.01	-0.00	0.01
	(0.01)	(0.02)	(0.02)
Log Hrs/Week x	-0.21		
1991-2000	(0.26)		
Ever Part-Time	-0.01		
x 1991-2000	(0.09)		
Ever Not Emp. x	0.01		
1991-2000	(0.04)		
Years Part-Time	0.05		
x 1991-2000	(0.05)		
Years Not Emp.	-0.05		
x 1991-2000	(0.05)		
Years Prac. Law	0.04***		
x 1991-2000	(0.01)		
Log Hrs/Week	0.47**	0.53**	0.26
	(0.19)	(0.19)	(0.17)
Ever Part-Time	-0.08	-0.08	-0.09***
	(0.07)	(0.07)	(0.02)
Ever Not Emp.	-0.06	-0.06	-0.06**
	(0.05)	(0.05)	(0.03)
Years Part-Time	-0.22***	-0.22***	-0.16***
	(0.05)	(0.05)	(0.02)
Years Not Emp.	-0.23***	-0.24***	-0.26***
	(0.06)	(0.05)	(0.08)
Years Prac. Law	0.04***	0.04***	0.07***
	(0.01)	(0.01)	(0.01)
Constant	6.84**	2.99	10.98***
	(2.17)	(3.04)	(3.16)
Age, Age Squared	Yes	Yes	Yes
Race Dummies	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Undergraduate Controls	Yes	Yes	Yes
Law School Controls	Yes	Yes	Yes
Workplace Setting	Yes	Yes	Yes
Non-Practice Setting	Yes	Yes	Yes
Observations	3702	1865	1837
R^2	0.516	0.553	0.499

Outcome is log annual earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Sample includes all survey respondents from the classes of 1982-2000 currently in the labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values and whether transfer student included but not reported. Controls for log weeks per year included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Table 2.10: Changes in Career Cost of Family Over Time, 15th Year Survey

	(1) All	(2) 1972-1980	(3) 1981-1991
Female	-0.06**	-0.07	-0.05*
	(0.03)	(0.05)	(0.02)
Log Hrs/Week x	-0.07		
1981-1991	(0.10)		
Ever Part-Time	0.08		
x 1981-1991	(0.06)		
Ever Not Emp. x	0.16***		
1981-1991	(0.04)		
Years Part-Time	-0.02		
x 1981-1991	(0.02)		
Years Not Emp.	-0.09**		
x 1981-1991	(0.03)		
Years Prac. Law	0.00		
x 1981-1991	(0.00)		
Log Hrs/Week	1.02***	1.07***	0.93***
	(0.08)	(0.09)	(0.10)
Ever Part-Time	-0.24**	-0.27***	-0.16***
	(0.07)	(0.07)	(0.05)
Ever Not Emp.	-0.18***	-0.19***	-0.02
	(0.04)	(0.06)	(0.04)
Years Part-Time	-0.03	-0.02	-0.05***
	(0.02)	(0.02)	(0.01)
Years Not Emp.	-0.02	-0.04	-0.11***
	(0.03)	(0.04)	(0.02)
Years Prac. Law	0.02***	0.02***	0.01**
	(0.00)	(0.00)	(0.00)
Constant	2.37	4.73	-0.07
	(3.99)	(7.05)	(9.67)
Age, Age Squared	Yes	Yes	Yes
Race Dummies	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Undergraduate Controls	Yes	Yes	Yes
Law School Controls	Yes	Yes	Yes
Workplace Setting	Yes	Yes	Yes
Non-Practice Setting	Yes	Yes	Yes
Observations	3631	1848	1783
R^2	0.520	0.498	0.549

Outcome is log annual earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Sample includes all survey respondents from the classes of 1972-1991 currently in the labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values and whether transfer student included but not reported. Controls for log weeks per year included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Hours worked per week is strongly correlated with earnings at all stages of the career. The relationship between hours per week and earnings is concave at five years ($\beta = 0.5 < 1$) and linear at 15 years.[2] When controls for previous experience are included, the effect of an increase in hours per week on earnings does not generally depend on the number of hours, except for extremely long work weeks at 15 years for which there is slight evidence of decreasing returns to increased hours. The returns to longer hours do not differ for full-time and part-time workers.

In the fifth year surveys, the earnings penalty for part-time work and non-work is linear and constant over the survey period. The coefficient on having a spell of either non-work or part-time work that is six months or longer is not statistically different from zero, while each year of part-time or non-work will cost a man or woman a whopping 21 to 23 log points of earnings. There is substantial change in the structure of the earnings penalty for spells of non-work 15 years after graduation. In the first decade, any spell of non-work of six months or longer reduces earnings by 18 log points, with almost no linear penalty, while in the second decade of the survey the penalty is 11 log points for each year of non-work with no discrete penalty. The cost of working part-time appears to also become more linear, but the coefficients on past labor supply variables are not statistically significantly different across decades. In all cases, the type of work matters: each year spent practicing law is correlated with higher earnings controlling for time spent working.

From the first to second decade of the 15-year survey, the earnings penalty for taking between six months and two years out of the labor force decreased. Unsurprisingly, this coincided with an increase in the fraction of women reporting spells of non-work of six months or longer; in the average years reported not working; and in the fraction of women and men reporting being out of the labor force at the time of the survey (Table 2.4). In the next section, I explore the relationship between family and marriage market outcomes and this decrease in labor supply.

[2] While current earnings and hours per week have a concave relationship, this certainly does not take in to account the expected payoff from making partner in the future.

2.4.5 A Preliminary Explanation

Why might the discrete penalty for spells of non-work decreased over this time period? Some evidence of increased labor supply flexibility in law firms and corporate settings can be drawn from the job titles and workplace settings of respondents who report working part-time at the time of the survey (Table 2.11). In the 1972-1980 15-year cohort, part-time workers are largely solo practitioners or in a non-practicing, "other" position. They are much less likely than full-time workers to be partners at a firm with more than one lawyer or corporate counsel. In the 1981-1991 cohort, however, part-time workers have infiltrated a wider spectrum of law jobs. The fraction in solo practice has decreased dramatically, far outstripping the decrease in the fraction of full-time lawyers in solo practice. Part-time workers are almost as likely as full-time workers to be corporate counsel. In multi-lawyer firms, one can see the creation of the role of "part-time partner" as well as a slight increase in "other", which includes of counsel and other more senior, non-partner positions within firms.

Workers with prior spells of non-work now have jobs more similar to those with continuous labor force participation in the second decade than they did in the first (Table 2.12). Because of the rise in the "non-practice" category for both workers with and without non-work spells, it is difficult to determine how this shift in workplace setting has affected the penalty for non-work calculated in the previous section.

2.5 Career, Family, and Labor Supply

The previous section established two facts. First, for those lawyers in the labor force, demographics, law school performance, work history, and job type are largely suffient for explaining the gender gap in earnings. Second, there is some evidence that the earnings penalty for spells of non-work has shifted from a discrete cost for any spell over six months to a linear cost proportional to years not working over the course of the survey period.

In this section, I investigate to what extent marriage market patterns interact with fertility

Table 2.11: Workplace Setting and Attorney Status of Lawyers by Labor Supply, 15th Year Survey

(a) Workplace Setting of Lawyers by Part-Time Status

	1972-1980				1981-1991				
	Part-Time		Full-Time		Part-Time		Full-Time		
Law Firm	40	56%	1203	63%	77	45%	900	50%	
Corporate Counsel	1	1%	216	11%	17	10%	275	15%	s
Govt/LS	7	10%	174	9%	18	11%	193	11%	
Not Practicing	21	29%	289	15%	50	29%	379	21%	
Missing	3	4%	20	1%	9	5%	44	2%	

(b) Attorney Status of Firm Lawyers by Part-Time Status

	1972-1980				1981-1991			
	Part-Time		Full-Time		Part-Time		Full-Time	
Solo	24	60%	103	9%	17	22%	75	8%
Partner	5	13%	1009	84%	23	30%	646	72%
Associate	3	8%	52	4%	11	14%	42	5%
Other	5	13%	31	2%	13	17%	58	6%
Missing	3	8%	8	1%	13	17%	79	9%

Sample includes all survey respondents from the classes of 1972-1991 currently in labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

Table 2.12: Workplace Setting and Attorney Status of Lawyers by Non-Work Spells, 15th Year Survey

(a) Workplace Setting of Lawyers by Non-Work Status

	1972-1980				1981-1991			
	Ever Not Worked		Never Not Worked		Ever Not Worked		Never Not Worked	
Law Firm	73	47%	1,156	64%	121	43%	853	51%
Corporate Counsel	17	11%	197	11%	33	12%	259	16%
Govt/Pub. Serv.	21	13%	158	9%	43	15%	167	10%
Not Practicing	40	26%	268	15%	75	27%	344	21%
Missing	5	3%	17	1%	7	4%	45	3%

(b) Attorney Status of Firm Lawyers by Non-Work Status

	1972-1980				1981-1991			
	Ever Not Worked		Never Not Worked		Ever Not Worked		Never Not Worked	
Solo	19	26%	101	9%	19	16%	72	8%
Partner	34	47%	973	84%	52	43%	615	72%
Associate	12	16%	43	4%	20	17%	33	4%
Other	7	10%	29	3%	18	15%	53	6%
Missing	1	1%	10	1%	12	10%	80	9%

Sample includes all survey respondents from the classes of 1972-1991 currently in labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

and labor supply decisions to explain the changes in labor supply discussed in the introduction. Marriage market matching may be important in determining who is "opting out" of the labor market and who chooses to stay in. The implications of the composition of this group are very different depending on who is "opting out": if the highest-ability women are choosing not to work, this margin may provide an explanation for the lack women partners at top law firms, whereas the lowest-ability women opting out may signal gender-based discrimination.

2.5.1 Predicted Earnings

A woman's reported earnings at the time of the surveys are a poor meausure of whether she is potentially high-earning, as they are potentially the equilibrium outcome of current and prior family and labor supply decisions. I thus begin by constructing a measure of "potential earnings" for women. This is intended to approximate the woman's earnings if she had worked full-time since graduation from law school without any reduced hours or job interruptions. I then use this measure to examine how career and family tradeoffs vary by a woman's earnings potential.

I predict earnings potential as a function of law school characteristics and first-year job characteristics and earnings. Because men in this sample have virtually no labor force participation reductions and report almost no career interruptions (Table 2.4), they provide excellent proxies for "as if" of full labor force participation. Moreover, the analysis of the gender gap in earnings from the previous section indicated that differences in observables, rather than coefficients, explain the differences in earnings between men and women. I thus estimate a model of earnings in the survey year as a function of law school and first year characteristics using the data from male respondents and set a woman's potential earnings to be her expected earnings given these estimates.

Specifically, I estimate

$$y_i = \beta_0 + \beta_1 y_{i1} + \gamma' F_i + \delta' L_i + \nu' P_i + \alpha' U_i + \omega' X_i + \iota' D_{jdyr} + \epsilon_i$$

where y_i is log earnings at the time of the survey, y_{i1} is log earnings the first year after law school graduation, F_i are indicators for the type of first job (law firm, corporate, or government/public service), L_i are law school performance measures including law school GPA, LSAT percentile, and whether a transfer, U_i are undergraduate GPA and institution, X_i are individual characteristics including age, age squared, and ethnicity, and D_{jdyr} is a vector of graduation-year fixed effects.

Considerations of career and family may still systematically bias this estimate of earnings potential if women alter their school performance and choice of first job in anticipation of the marriage market or of the demands of having children (see for example Benson (2011)). While women have lower law school GPAs than their male counterparts, they are almost equally likely to have a first job in a private firm (58.99% for men vs. 54.88% for women). They are also equally likely to report a long-term career plan of working at a large law firm (26.16% of men vs. 26.28% of women) which is one of the most lucrative and demanding career paths for elite law graduates. Along these dimensions, the women graduates match men graduates in their career ambitions.

Estimates of the earnings equation are given in Table 2.13. Log first year earnings, type of first job, law school GPA, and undergraduate GPA strongly and significantly predict both five and 15 year earnings. Including first-year earnings and job type adds substantial explanatory power to the regression even conditioning on law school performance.

Table 2.13: Estimating Earnings Potential Using School Performance and First Job Characteristics

	(1) 5th Year	(2) 5th Year	(3) 15th Year	(4) 15th Year
Law School GPA	0.18***	0.14***	0.21***	0.16***
	(0.01)	(0.01)	(0.02)	(0.02)
LSAT Percentile	-0.00	-0.00	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Undergraduate	-0.04***	-0.03**	-0.04**	-0.03**
GPA	(0.01)	(0.01)	(0.02)	(0.02)
Transfer	0.06	-0.01	0.01	-0.06
Student	(0.06)	(0.05)	(0.08)	(0.07)
First Job		0.11		-0.09
Corporate		(0.07)		(0.07)
First Job		-0.25***		-0.39***
Govt/Pub Serv		(0.04)		(0.04)
First Job Other		-0.01		-0.38***
		(0.08)		(0.06)
Log 1st Year		0.42***		0.38***
Income		(0.03)		(0.09)
Constant	15.36***	8.81***	11.89***	7.72**
	(3.17)	(2.85)	(3.36)	(3.39)
Age, Age Squared	Yes	Yes	Yes	Yes
Race Dummies	Yes	Yes	Yes	Yes
Undergraduate School	Yes	Yes	Yes	Yes
Observations	2377	2377	2847	2847
R^2	0.149	0.328	0.107	0.199

Outcome is log annual earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Sample includes all male survey respondents from the classes of 1982-2000 (5th year) and 1972-1991 (15th year) currently in the labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Because the earnings potential measure is estimated, standard errors reported in ordinary least squares regressions will be incorrect. All regressions include standard errors clustered by census region. The appropriate method would be to use a nonparametric bootstrap to compute standard errors for all reported regressions.

2.5.2 Trends Over Time

Later graduates of UMLS are delaying both marriage and fertility compared to their senior counterparts. The fraction of both women and men that report being married and ever married (including divorced, widowed, and separated) 15 years after graduation has not changed over the course of the survey period (Figure 2.7). However, the fraction married for men and, particularly, women prior to law school, at law school graduation, and five years after graduation has steadily declined. Even more striking is the delay in childbearing: while the fraction of graduates with children at the 15-year survey has remained constant over time, graduates are increasingly delaying childbearing until more than five years after graduation (Figure 2.8).

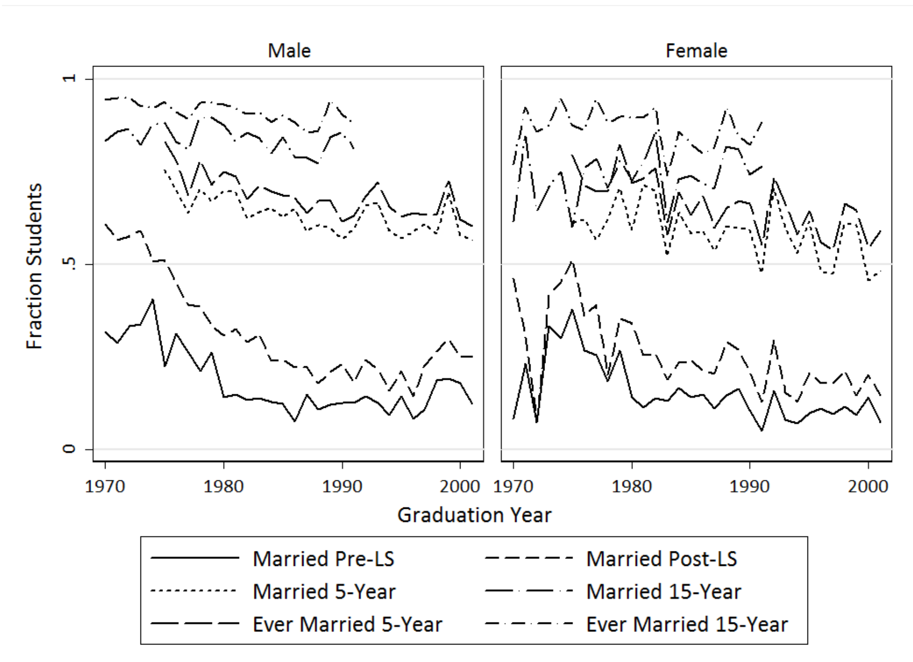

Figure 2.7: Probability of marital outcomes by gender and graduation year. Sample includes all survey respondents who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

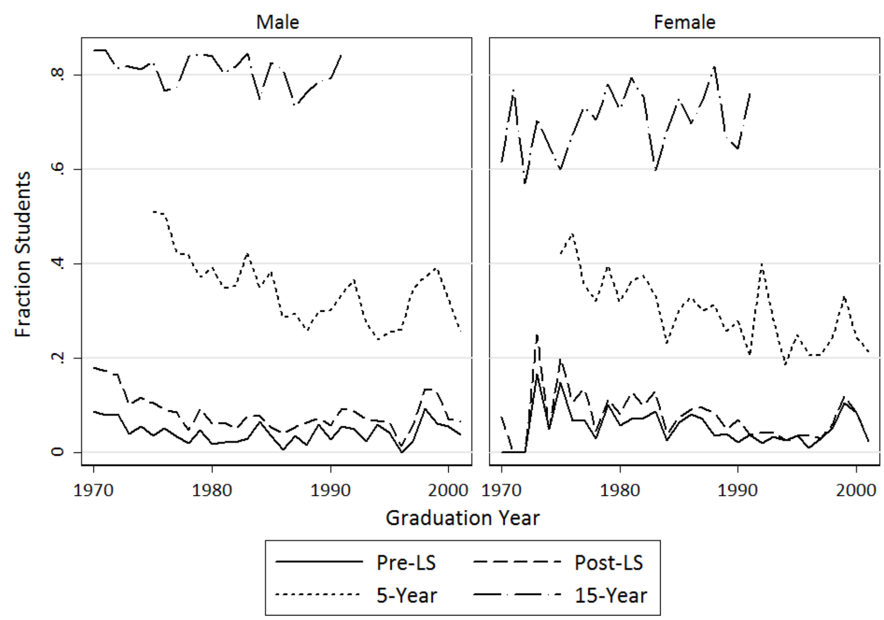

Figure 2.8: Probability of having children by gender and graduation year. Sample includes all survey respondents who graduated before age 31 and in less than six years. See Appendix B for variable definitions.

2.5.3 Selection in to Marriage and Spouse Choice

I begin by estimating the relationship between earnings potential, selection in to marriage, and assortative mating conditional on marriage. In both survey waves, between 5% and 10% of the respondents report being unmarried but having a live-in partner for whom they report occupation and earnings data. Through this section I define “marriage” to be either married or in such a cohabiting relationship.

Let m_i be a marriage-related variable such as whether individual i is married or the log income of individual $i's$ spouse. I estimate regressions of the form

$$m_i = \beta_0 + \beta_1 \hat{y}_i + \beta \cdot X_i + d_{jdyr} + \epsilon_i$$

where $\hat{y}_i$ is individual $i's$ earnings potential as predicted above; X_i are controls that may include type of undergraduate institution, race, and location characteristics in the survey year; d_{jdyr} are year of graduation dummies; and ϵ_i is an error. The individual characteristics X_i are controls that may affect marriage market outcomes directly as well as through earnings potential. Including these as controls indicates to what extent they mediate the correlation between earnings potential and the outcome of interest. Characteristics such as law school grades and LSAT scores that should impact marriage market oucomes only through potential earnings are included only in the estimate of earnings potential $\hat{y}_i$.

Tables 2.14 and 2.15 reports regressions for outcomes measured five years after law school graduation. Both women and men with higher earnings potential are more likely to be married. Conditional on having a spouse in the labor force, individuals with higher earnings potential have higher-earning spouses.

Controlling for census region and city population increases the conditional correlation between earnings potential and the probability of being married and decreases the correlation between earnings potential and spouse earnings. Both men and women who live in very large cities (defined as a population of over three million) are ten percent less likely to be married five years after graduation, but conditional on marriage their spouses have higher earnings. This delay of marriage may be due to the higher density of potential partners in large cities and resulting longer search time, or perhaps due to individuals in cities working longer hours and having correspondingly higher earnings.

Tables 2.16 and 2.17 replicate the analysis for marriage outcomes 15 years post-graduation. Respondents with higher earnings potential and white respondents are both uniformly more likely to be married. Conditional on marriage, however, the correlation between earnings potential for men and spouse earnings is no longer significantly different from zero. If one assumes that the husbands of female respondents have not changed their labor supply in response to the demands of family or their spouses' characteristics, and hence that husband earnings are a proxy for husband earnings potential, these results suggest that lawyers even within this elite group are marrying assortatively on earnings potential. Because earnings are a function of both law school performance and job choice, it is not clear to what extent search frictions or preferences

Table 2.14: Whether Married, 5th Year Survey

	(1) All	(2) Women	(3) Men	(4) All	(5) Women	(6) Men	(7) All	(8) Women	(9) Men
Female	-0.80			-0.79			-0.75		
	(0.64)			(0.64)			(0.65)		
Earnings	0.12***	0.17***	0.12***	0.12***	0.17***	0.13***	0.17***	0.22***	0.18***
Potential	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Female x	0.07			0.07			0.06		
Earnings Potential	(0.06)			(0.06)			(0.06)		
Constant	-0.66	-1.36***	-0.65	-5.17*	-7.53	-4.65	-5.28*	-8.46*	-4.52
	(0.41)	(0.52)	(0.41)	(2.84)	(4.64)	(3.63)	(2.85)	(4.64)	(3.63)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	4117	1533	2584	4117	1533	2584	4117	1533	2584
R^2	0.018	0.032	0.014	0.032	0.054	0.032	0.052	0.075	0.054

Linear probability models with dependent variable = 1 if respondent reports being married at the time of the survey. Earnings in 2007 dollars. Earnings potential predicted using estimates from Table 2.13. Significant at: * 10%; ** 5%; *** 1%. Sample includes all survey respondents from the classes of 1982-2000 who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Table 2.15: Spouse Earnings, 5th Year Survey

	(1) All	(2) Women	(3) Men	(4) All	(5) Women	(6) Men	(7) All	(8) Women	(9) Men
Female	2.19			2.21			2.23		
	(1.95)			(1.95)			(1.93)		
Earnings	0.52***	0.37**	0.52***	0.55***	0.35**	0.58***	0.44***	0.23	0.47***
Potential	(0.08)	(0.16)	(0.08)	(0.09)	(0.16)	(0.09)	(0.09)	(0.16)	(0.09)
Female x	-0.14			-0.14			-0.14		
Earnings Potential	(0.17)			(0.17)			(0.17)		
Constant	4.74***	7.06***	4.69***	-9.43	-0.60	-15.50	-8.97	-2.42	-13.71
	(0.98)	(1.86)	(0.98)	(7.55)	(9.48)	(10.21)	(7.57)	(9.08)	(10.44)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	2225	836	1389	2225	836	1389	2225	836	1389
R^2	0.123	0.043	0.044	0.130	0.048	0.064	0.162	0.103	0.094

Outcome is log spouse earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Earnings potential predicted using estimates from Table 2.13. Sample includes all married survey respondents from the classes of 1982-2000 with non-missing and non-zero spouse earnings who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

for similarly-abled spouses with similar occupations leads to this positive assortative mating on earnings. The positive correlation between the earnings potential of men and their wives' earnings at five years which disappears at 15 years is most likely explained by wives of men with high earnings potential reducing their labor supply to care for children.

2.5.4 Fertility

Most women in the sample who have children have them between the 5 and 15 year surveys: 28% of women report having children 5 years after graduation, while 70% have children 15 years after. Table 2.19 reports correlations between having children by year 15 and the individual characteristics of parents. Out-of-wedlock childbearing is virtually nonexistent in this sample, so I restrict this sample to married men and women. Women and men with higher earnings potential are no more likely to have children. However, there is a positive and significant correlation between a woman's fertility and her spouse's reported earnings. Women with higher-earning husbands are more likely to report having children, and they have more children conditional on having any (Tables 2.18 and 2.19). The coefficients on spousal earnings for men have the opposite sign. Men whose wives report lower earnings are more likely to have kids and have more of them. Given the estimates for women, these negative coefficients are mostly likely due to wives of high-earning men reducing their labor supply to care for children.

The coefficients on spouse earnings shows the impact that positive assortative mating on earnings potential has on the fertility of women in the sample. Women with high earnings potential are more likely to have children as the probability of having children and the number of children are increasing in spouse earnings. In the next section I show the implications of this increase in fertility for the labor supply of these high-ability women.

2.5.5 Labor Supply

Fifteen years after graduation, only 66% of women report working full-time in the labor force. The primary driver of this is the presence of children: Figure 2.2 shows that a woman with one

Table 2.16: Whether Married, 15th Year Survey

	(1) All	(2) Women	(3) Men	(4) All	(5) Women	(6) Men	(7) All	(8) Women	(9) Men
Female	-0.40			-0.30			-0.37		
	(0.47)			(0.42)			(0.42)		
Earnings	0.13***	0.15**	0.13***	0.09***	0.12**	0.09***	0.10***	0.14**	0.10***
Potential	(0.01)	(0.05)	(0.01)	(0.01)	(0.05)	(0.02)	(0.01)	(0.06)	(0.02)
Female x	0.03			0.02			0.03		
Earnings Potential	(0.04)			(0.03)			(0.03)		
Constant	-0.66***	-1.02	-0.72***	-0.35	1.20	-1.75	-0.36	0.08	-1.38
	(0.15)	(0.58)	(0.11)	(2.79)	(8.58)	(2.86)	(2.80)	(8.29)	(3.08)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	4228	1035	3193	4228	1035	3193	4228	1035	3193
R^2	0.031	0.034	0.024	0.050	0.086	0.037	0.057	0.115	0.046

Linear probability models with dependent variable = 1 if respondent reports being married at the time of the survey. Earnings in 2007 dollars. Earnings potential predicted using estimates from Table 2.13. Significant at: * 10%; ** 5%; *** 1%. Sample includes all survey respondents from the classes of 1972-1991 who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Table 2.17: Spouse Earnings, 15th Year Survey

	(1) All	(2) Women	(3) Men	(4) All	(5) Women	(6) Men	(7) All	(8) Women	(9) Men
Female	-6.09***			-6.27***			-7.43***		
	(1.46)			(1.32)			(1.17)		
Earnings	0.10	0.76***	0.05	0.08	0.64***	0.09	-0.04	0.65***	-0.05
Potential	(0.09)	(0.09)	(0.11)	(0.10)	(0.08)	(0.11)	(0.08)	(0.06)	(0.09)
Female x	0.59***			0.61***			0.70***		
Earnings Potential	(0.12)			(0.11)			(0.09)		
Constant	9.46***	2.52**	10.01***	12.31	29.11**	-1.01	10.25	26.15**	-1.87
	(1.12)	(1.06)	(1.27)	(8.03)	(10.48)	(14.61)	(7.10)	(10.52)	(13.90)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	2171	648	1523	2171	648	1523	2171	648	1523
R^2	0.206	0.100	0.037	0.211	0.128	0.048	0.244	0.169	0.093

Outcome is log spouse earnings in 2007 dollars. Significant at: * 10%; ** 5%; *** 1%. Earnings potential predicted using estimates from Table 2.13. Sample includes all married survey respondents from the classes of 1972-1991 with non-missing and non-zero spouse earnings who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Table 2.18: Has Children, 15th Year Survey

	(1) All	(2) Women	(3) Men	(4) All	(5) Women	(6) Men	(7) All	(8) Women	(9) Men
Female	-0.33			-0.33			-0.30		
	(0.61)			(0.58)			(0.55)		
Earnings	0.05*	0.07*	0.05*	0.04	0.06	0.04	0.04	0.05	0.05*
Potential	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
Female x	0.02			0.02			0.02		
Earnings Potential	(0.05)			(0.05)			(0.05)		
Log Spouse	-0.06***	0.04***	-0.06***	-0.06***	0.03**	-0.06***	-0.05***	0.03**	-0.05***
Income	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female x Log	0.09***			0.09***			0.09***		
Spouse Income	(0.01)			(0.01)			(0.01)		
Constant	0.41	-0.07	0.37	-5.47	-7.17	-5.65	-6.23*	-7.83	-6.19
	(0.28)	(0.39)	(0.27)	(3.41)	(9.63)	(3.36)	(3.31)	(9.38)	(3.52)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3644	834	2810	3644	834	2810	3644	834	2810
R^2	0.061	0.043	0.070	0.066	0.059	0.075	0.075	0.072	0.086

Linear probability models with dependent variable = 1 if respondent reports having one or more children at the time of the survey. Earnings in 2007 dollars. Earnings potential predicted using estimates from Table 2.13. Significant at: * 10%; ** 5%; *** 1%. Sample includes all married survey respondents from the classes of 1972-1991 who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. Controls for married, spouse income missing and married, spouse earns no income included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Table 2.19: Number of Children, 15th Year Survey

	(1) All	(2) Women	(3) Men	(4) All	(5) Women	(6) Men	(7) All	(8) Women	(9) Men
Female	0.73			0.67			0.85		
	(1.74)			(1.73)			(1.86)		
Earnings	0.15*	0.07	0.16*	0.17	0.10	0.18	0.19*	0.08	0.21*
Potential	(0.08)	(0.12)	(0.08)	(0.11)	(0.13)	(0.10)	(0.10)	(0.13)	(0.09)
Female x	-0.05			-0.05			-0.06		
Earnings Potential	(0.15)			(0.15)			(0.16)		
Log Spouse	-0.11***	0.12***	-0.10***	-0.10***	0.11***	-0.10***	-0.09***	0.12**	-0.09***
Income	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)
Female x Log	0.22***			0.21***			0.21***		
Spouse Income	(0.04)			(0.04)			(0.05)		
Constant	0.56	1.20	0.40	-3.18	-4.65	-1.88	-4.11	0.37	-5.01
	(0.95)	(1.40)	(0.91)	(12.08)	(13.78)	(13.18)	(11.94)	(13.66)	(14.31)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3156	686	2470	3156	686	2470	3156	686	2470
R^2	0.046	0.049	0.046	0.053	0.061	0.053	0.071	0.083	0.074

Earnings in 2007 dollars. Earnings potential predicted using estimates from Table 2.13. Significant at: * 10%; ** 5%; *** 1%. Sample includes all married survey respondents from the classes of 1972-1991 with one ore more children who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. Controls for married, spouse income missing and married, spouse earns no income included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

more children is 30% less likely to work full time than a woman who does not. In this section, I investigate the relationship between fertility and relative earnings in determining the labor supply of these professional men and women.

I first estimate the correlation between labor force participation and family characteristics in Table 2.20. Because only 1% of men report being out of the labor force in the 15 year survey, there is no variation to explain using demographics and fertility, and coefficients of the regression of a husband being out of the labor force on his and his wife's characteristics produces nothing of interest. A woman's probability of not currently working is increasing in the earnings of her husband if she has children, and in the number of children conditional on having any. Spouse characteristics have no impact on labor force participation if the couple does not have children. Thus, women with higher earnings potential are indirectly more likely to be out of the labor force via two channels: they have higher-earning spouses, and they have more children on average due to their higher-earning husbands. The effect of high-earning spouses on the extensive margin of labor supply was noted for MBAs by Bertrand et al. (2010).

Table 2.21 estimates the effect of earnings potential and fertility on the intensive margin of labor supply for women reporting that they are in the labor force. I use log of hours worked per week as the measure of current labor supply. All three of own potential earnings, spouse earnings, and fertility are important predictors of hours worked per week. A woman's weekly labor supply is increasing in her own expected earnings in all cases and decreasing in her spouse's earnings if she has children. Conditional on having any children, an additional child results in a decrease in labor supply of 11 log points. Correlations between family characteristics and and labor supply are not mediated by demographic or location controls.

Tables 2.20 and 2.21 also estimate the relationship between labor supply and family characteristics broken down by decade. On the extensive margin for women, there has been little change over the two decades in question. The number of children has an effect on the extensive margin of labor supply only in the second decade, but controlling for age, race, and location, the effect of spouse income on the extensive margin of labor supply remains the same. On the other hand,

Table 2.20: Probability of Not Working for Women, 15th Year Survey

	(1) All	(2) 1972-1980	(3) 1981-1991	(4) All	(5) 1972-1980	(6) 1981-1991	(7) All	(8) 1972-1980	(9) 1981-1991
No Children x	-0.10**	-0.13	-0.07	-0.13**	-0.15	-0.08	-0.10*	-0.17*	-0.04
Earnings Potential	(0.05)	(0.10)	(0.05)	(0.05)	(0.10)	(0.06)	(0.06)	(0.10)	(0.06)
Has Children x	-0.03	0.05	-0.07	-0.04	0.03	-0.08	-0.03	0.05	-0.08
Earnings Potential	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)
No Children x	-0.01	-0.00	-0.00	-0.01	0.00	-0.01	-0.01	0.00	0.00
Log Spouse Income	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Has Children x	0.08***	0.05*	0.08***	0.08***	0.05*	0.09***	0.08***	0.06**	0.08***
Log Spouse Income	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Has Children	-0.69	-2.04	0.30	-0.83	-2.15	0.27	-0.72	-2.62*	0.68
	(0.81)	(1.30)	(0.94)	(0.81)	(1.34)	(0.95)	(0.83)	(1.33)	(0.96)
2 Children	0.07**	0.00	0.10**	0.07**	0.00	0.09**	0.09***	0.01	0.11**
	(0.03)	(0.05)	(0.04)	(0.03)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)
3 Children	0.12**	0.04	0.14**	0.12**	0.05	0.13**	0.13***	0.07	0.14**
	(0.05)	(0.07)	(0.06)	(0.05)	(0.08)	(0.06)	(0.04)	(0.07)	(0.06)
4+ Children	0.19***	0.14	0.22**	0.20***	0.15	0.21**	0.19***	0.16	0.18**
	(0.07)	(0.12)	(0.09)	(0.07)	(0.12)	(0.09)	(0.07)	(0.11)	(0.09)
Constant	1.45**	1.50	1.03	-5.97	-5.88	-7.35	-3.23	-5.81	-5.74
	(0.64)	(1.20)	(0.66)	(5.99)	(5.86)	(8.93)	(6.14)	(6.22)	(9.13)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1000	328	672	1000	328	672	1000	328	672
R^2	0.201	0.122	0.213	0.209	0.130	0.223	0.276	0.272	0.293

Linear probability model with outcome = 1 if respondent reports not being in labor force at the time of survey. Earnings in 2007 dollars. Earnings potential predicted using estimates from Table 2.13. Significant at: * 10%; ** 5%; *** 1%. Sample includes all married female survey respondents from the classes of 1972-1991 who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. Controls for married, spouse income missing and married, spouse earns no income included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

Table 2.21: Weekly Labor Supply of Women, 15th Year Survey

	(1) All	(2) 1972-1980	(3) 1981-1991	(4) All	(5) 1972-1980	(6) 1981-1991	(7) All	(8) 1972-1980	(9) 1981-1991
No Children x	0.10**	0.07	0.08	0.21***	0.22**	0.19***	0.19***	0.23**	0.13**
Earnings Potential	(0.04)	(0.06)	(0.05)	(0.03)	(0.07)	(0.04)	(0.03)	(0.07)	(0.05)
Has Children x	0.13***	0.08*	0.15*	0.21***	0.18**	0.20**	0.16***	0.16*	0.15*
Earnings Potential	(0.04)	(0.04)	(0.08)	(0.02)	(0.06)	(0.08)	(0.02)	(0.07)	(0.07)
No Children x	-0.03	0.01	-0.05	-0.03	-0.02	-0.04	-0.04	-0.01	-0.07
Log Spouse Income	(0.04)	(0.02)	(0.05)	(0.04)	(0.02)	(0.06)	(0.05)	(0.02)	(0.06)
Has Children x	-0.07**	-0.01	-0.09***	-0.06**	0.00	-0.07***	-0.07**	-0.00	-0.08***
Log Spouse Income	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.05)	(0.02)
Has Children	-0.44	-0.49	-0.81	0.10	0.16	0.05	0.35	0.46	-0.11
	(0.60)	(0.88)	(0.61)	(0.49)	(0.50)	(0.70)	(0.38)	(0.46)	(0.63)
2 Children	-0.12**	0.03	-0.20***	-0.11**	0.02	-0.18**	-0.10**	0.03	-0.18**
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.03)	(0.04)	(0.07)
3 Children	-0.23***	-0.02	-0.33***	-0.23***	-0.08	-0.31***	-0.22***	-0.07	-0.31***
	(0.04)	(0.08)	(0.05)	(0.04)	(0.09)	(0.05)	(0.03)	(0.09)	(0.04)
4+ Children	-0.36**	-0.30	-0.38***	-0.34***	-0.33*	-0.36**	-0.31**	-0.28	-0.34**
	(0.12)	(0.17)	(0.11)	(0.10)	(0.16)	(0.11)	(0.10)	(0.17)	(0.13)
Constant	2.51***	3.07***	2.71***	5.33	17.32	0.83	5.17	15.25	-0.00
	(0.32)	(0.73)	(0.56)	(4.91)	(10.02)	(7.21)	(5.28)	(12.19)	(6.35)
Age, Age Squared	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race Dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Undergraduate School	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	853	302	551	853	302	551	853	302	551
R^2	0.161	0.138	0.174	0.182	0.215	0.193	0.212	0.247	0.231

Outcome is log hours worked per week. Earnings in 2007 dollars. Earnings potential predicted using estimates from Table 2.13. Significant at: * 10%; ** 5%; *** 1%. Sample includes all married female survey respondents from the classes of 1972-1991 in the labor force who graduated before age 31 and in less than six years. See Appendix B for variable definitions. Dummy variables for missing values included but not reported. Controls for married, spouse income missing and married, spouse earns no income included but not reported. All regressions include year of graduation fixed effects. Standard errors clustered by census region included in parentheses.

the large effects of respondent and spouse characteristics and fertility on hours worked per week is only visible in the second decade of the 15 year survey. Family characteristics have no impact on the intensive margin for women graduating in the 1970s.

Together, this table suggests that the decrease in the cost of reduced labor supply led to a decrease in labor supply disproportionately among women with high earnings potential, who took advantage of the decreased constraints on labor supply flexibility in the later half of the survey to purchase a bundle of high-paying work with flexible labor supply, a family, and a high-earning spouse.

2.6 The Curse of Positive Assortative Mating

If one wishes to maximize the labor force participation of workers with high human capital, the observation of positive assortative mating amongst these highly-educated lawyers poses a bit of a conundrum. If specialization within the family is efficient, negative assortative mating on earnings potential is the socially efficient outcome (Becker, 1973). Indeed, the positive assortative matching we observe is the marriage market outcome that *minimizes* the probability that the highest-ability women remain in the labor force. Moreover, introducing family-friendly flexibility in to previously unfriendly enviroments results in reductions in labor supply by exactly the women that we would wish to be working as much as possible. Thus, if there is some conscious tradeoff between career and family in choosing a spouse, it is confusing as to why women who invest so much in high-quality human capital all the way through professional school would choose combinations of spouses and fertility outcomes that would minimize their labor supply.

Examining detailed data on earnings potential, family outcomes, and marriage outcomes, however, a new potential picture emerges. It appears that some of the highest-ability women are using their high earnings potential to purchase a portfolio of goods which one might call "career, family, and spouse." Their high earnings potential allows them to meet, attract, and marry a high-earning spouse. With the couple's joint high income, they can have (and have more) children and, if needed, the woman can choose to work part time or not at all to spend more time with her children.

Much remains to be disaggregated in this detailed, rich data. In particular, this raises the question of whether the women who purchase work-life balance enter law school with this intention, or whether some combination of workplace time demands and the preference changes accompanying childbirth cause them to deviate from more ambitious career paths. In addition, these results raise an interesting question: do we see the most career-oriented women choosing to forego rich husbands in order to be the breadwinner and leading spouse? And is this a necessary condition to get to the top?

Chapter 3

Evaluating Econometric Models of Peer Effects with Experimental Data

3.1 Introduction

Models of social interaction effects frequently use means of peer characteristics to summarize peer group composition (Manski, 1993; Sacerdote, 2001; Zimmerman, 2003; Lyle, 2007; Graham, 2008; Carrell et al., 2009). The canonical linear-in-means model of peer effects popularized by Manski (1993) continues to be almost ubiquitous in the literature as it is theoretically tractible (Manski, 1993; Glaeser et al., 2003; Graham, 2008), computationally straightforward, and can accomodate many discrete or continuous peer characteristics. Motivated by the observation that a linear-in-means model with homogenous coefficients implies that peer group reassignment can have no impact on average outcomes (Hoxby and Weingarth, 2006), the linear-in-means model has been augmented with coefficients that vary by baseline ability, gender, or other characteristics (Hoxby, 2000; Carrell et al., 2011) and higher moments of the peer baseline ability distribution (Vigdor and Nechyba, 2007; Lyle, 2009). Recently, the mean has been used widely in network models of social interactions (Lee, 2007; Bramoullé et al., 2009; Boucher et al., 2010).

Recent econometric and experimental results, however, suggest that these standard empirical models of peer effects perform poorly with respect to both in-sample fit and counterfactual prediction. Carrell et al. (2011) estimate linear-in-means and linear-in-shares models of peer effects with heterogeneous coefficients using data from conditionally randomly assigned peer groups at the United States Air Force Academy. They experimentally implement the assignment of students to groups that maximizes the predicted achievement of the lowest-ability students in the school. Surprisingly, the low-ability students in their treatment group experience a statistically significant *decrease* in average performance compared to low-ability students in control (randomly-assigned) groups. Survey evidence suggests that the experimentally implemented peer groups reduced the opportunity for study partnerships between low-ability and middle-ability students, to the detriment of the low-ability students. In a concurrent literature, Imberman et al. (2009) and Hoxby and Weingarth (2006) use large natural experiments to nonparametrically estimate and perform specification tests for a variety of peer effects models; they reject linear-in-means models in favor of models in which all students benefit from homogenous classmates.

Despite the flourishing of both of these literatures, there has thus far been no systematic evaluation of which, if any, reduced-form peer effects specifications might accurately predict out-of-sample the impact of altering peer group assignment on outcomes. Following the seminal work of LaLonde (1986) and Dehejia and Wahba (2002), I use experimental data to perform such a comparison. Duflo et al. (2011) measure the impact of teacher incentives and classmate homogeneity on student achievement in a set of 121 elementary schools in Western Province, Kenya. Half of the schools in their sample were randomly selected to have two ability-tracked second grade classes ("tracking" or "treatment" schools), while the other half assigned students randomly to two classes per school ("non-tracking" or "control" schools). Duflo et al. (2011) found unambiguous evidence in favor of homogenous classes: students in both the top and bottom half of the within-school ability distribution showed statistically significant gains in endline test score from tracking. However, linear-in-means estimates from the randomly-assigned control group imply that tracking would be harmful to students in the bottom half of the ability distribution. Duflo et al. (2011) reconcile these results with a theoretical production function that combines direct peer effects generated by an increasing-in-means model with nonmonotonic indirect peer effects stemming from teacher responses to changes in class composition.

The theoretical framework of Duflo et al. (2011) relies crucially on functional form assumptions, and an experimenter with only the control group data would have difficulty estimating the indirect peer effects function and thus predicting the impact of reassignment on outcomes. I thus approach their experimental data with two, more reduced-form, questions. First, among both popular and non-standard econometric models of peer effects, which models would have best predicted the observed treatment effect from altering peer group composition? Second, would these models have been selected by standard model selection criteria? my approach is not as theoretically founded as that of Duflo et al. (2011): it does not distinguish between direct and indirect peer effects or explicitly model teacher response to class composition. However, it may be more applicable for experimental design, as inferring the impact of reassignment from randomly-assigned classes using reduced-form estimates has a long history in the peer effects literature (Sacerdote, 2001; Zimmerman, 2003; Lyle, 2007; Carrell et al., 2009; Lyle, 2009; Carrell et al., 2011).

I begin by using local linear regression to nonparametrically estimate the relationship between peer group composition and outcomes using data from the control schools and several different sets of summary statistics for peer group composition. The mean and standard deviation of peer baseline ability predict large losses from tracking for students in the bottom half of the ability distribution, while simple share-based nonparametric models have predictions that vary widely based on the number of student types specified. The median and interquartile range of peer baseline ability estimate that all students benefit from having more homogenous peers, which is consistent with the experimental outcome. The selection of summary statistics for peer group composition, largely taken for granted in the literature, thus appears to be a crucial step in choosing a peer effects model.

I then estimate a set of flexible linear specifications for each set of summary statistics above on the data from randomly-assigned classes. I find that a simple linear model using the median and interquartile range of peer baseline ability best predicts the experimental outcome, while the standard linear in moments model predicts large losses from tracking for low-ability students. Allowing coefficients to vary by initial ability or adding higher order terms worsens out-of-sample predictive accuracy and in some cases renders the peer group composition variables not statistically significant. Likelihood-based model selection criteria including the Bayesian information criterion have some success in selecting the models that best predict outcomes out of sample. Finally, I document the sensitivity of treatment effect predictions to summary statistic choice by varying the decile range used to measure peer ability dispersion.

my paper thus serves as a LaLonde-style warning about the precariousness of peer effects estimates and the need for the development of flexible peer effects specifications that perform well both in and out of sample. Theoretical models of peer effects vary widely in their implications for the impact of peer group composition on outcomes (Lazear, 2001; Hoxby and Weingarth, 2006). my analysis shows that in the absence of a clear choice of structural model of peer effects, the choice of how to summarize peer group composition in a reduced-form peer effects specification is not an innocuous one. Models that *ex ante* seem interchangeable provide opposing predictions of the impact of tracking on outcomes. Outlier-robust summary statistics and likelihood-based model selection criteria perform well in this setting; verifying the superior performance of these techniques in other settings is a worthy future endeavor.

my paper adds to an existing literature on specification choice in peer effects models. Graham et al. (2009, 2010) develop an innovative set of frameworks to estimate nonparametrically the impact of peer group composition on outcomes. Their classroom framework assumes that each individual is characterized by a binary characteristic, thus eliminating the decision of how to summarize peer group composition. Cascio and Schanzenbach (2007) compare a variety of summary statistics for peer group composition in the context of estimating the impact of the age distribution of a student's peers on outcomes. More generally, Manski (2011) establishes a framework for measuring treatment effects when the Stable Unit Treatment Value Assumption does not hold.

3.2 Data of Duflo et al. (2011)

3.2.1 Data Description

Duflo et al. (2011) experimentally measure the impact of class composition on the achievement of elementary school students in Western Province, Kenya. 121 elementary schools were provided funds by the World Bank to hire a second second-grade teacher. Duflo et al. (2011) randomly selected 61 schools to have two classes to which students were randomly-assigned within the school ("non-tracking" or "control" schools); in the remaining 60 schools, students were assigned to a high or low ability class based on their previous year's performance ("tracking" or "treatment" schools). Classes were randomly-assigned to facilities, including teachers, within schools. After eighteen months, a standardized end-of-year comprehensive written and oral examination was administered to students in all schools in the sample. For a more detailed description of the experiment and data, see Duflo et al. (2011).

Table 3.1 gives summary statistics for individual and class-level variables for the tracking and control schools. Individual characteristics observed are each student's class assignment, age at endline, gender, baseline exam score, and endline exam score. Baseline scores are available for 48 control schools and all 60 tracking schools; they are not comparable across schools and are are normalized to have zero mean and unit variance in each school. Endline test scores are comparable across all schools; scores are normalized so that control school outcomes have mean zero and unit variance. Tracking classes have on average 30 students with nonmissing baseline scores, while control classes have approximately 28.

Figures 3.1 and 3.2 show graphically the change in peer group composition, as measured by baseline test scores, induced by the experiment. Summary statistics for several measures of peer group composition are given in Table 3.1. Because scores are standardized by school and classes are randomly assigned within schools, identification in the control group is obtained from random variation in the split of below-average and above-average students within each school. [1]

[1] An alternate approach would be to exploit variation in baseline scores both within and between schools. Such

Table 3.1: Summary Statistics for Individual and Class-Level Variables

Individual Characteristics

	Non-Tracking	Tracking
Number of Students	3409	3613
Endline Score	0.00	0.14
	(1.00)	(1.02)
Baseline Score	0.02	0.00
	(0.99)	(0.99)
Age	9.18	9.36
	(1.46)	(1.47)
Female	0.49	0.50
	(0.50)	(0.50)

Peer Baseline Score Distributions

	Non-Tracking	Tracking
Mean	0.00	0.00
	(0.11)	(0.81)
Standard Deviation	1.00	0.58
	(0.08)	(0.16)
Median	-0.02	-0.02
	(0.23)	(0.75)
Interquartile Range	1.45	0.84
	(0.30)	(0.24)
Fraction Above Median	0.50	0.49
	(0.09)	(0.45)
Fraction Bottom Third	0.33	0.35
	(0.08)	(0.34)
Fraction Top Third	0.33	0.32
	(0.07)	(0.33)
Number of Peers	27.49	29.42
	(4.69)	(2.89)

Non-tracking schools are 61 schools in which students were assigned randomly to classes within schools. Tracking schools are 60 schools in which students were divided in to high and low ability classes by baseline score. Peer group composition statistics are for 48 non-tracking and 60 tracking schools with nonmissing baseline scores. Means are reported and standard deviations included in parentheses. Baseline test scores are normalized by school to have mean zero and unit variance. Endline score is normalized to have mean zero and unit variance in the non-tracking sample.

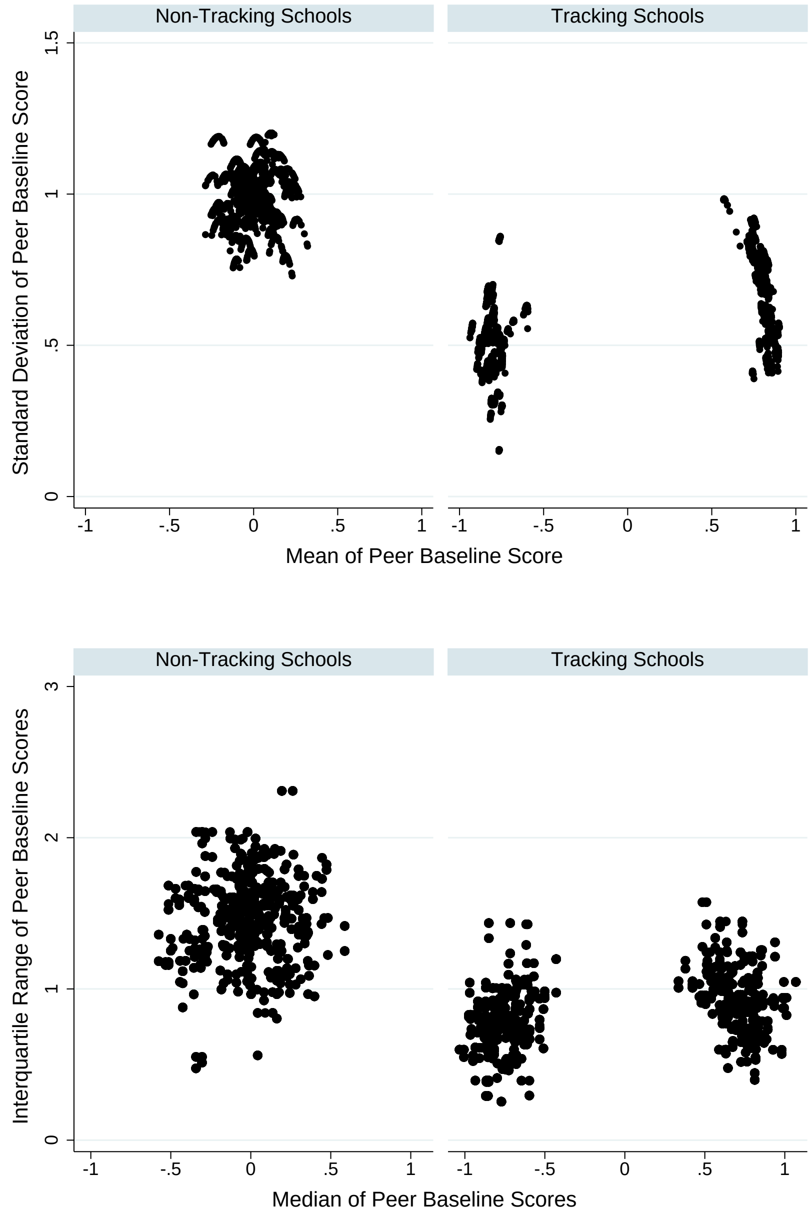

Figure 3.1: Change in class composition induced by the experiment. Summary statistics are for 48 non-tracking and 60 tracking schools for which baseline test score is nonmissing.

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an approach would require more information on the composition of baseline scores than is currently available.

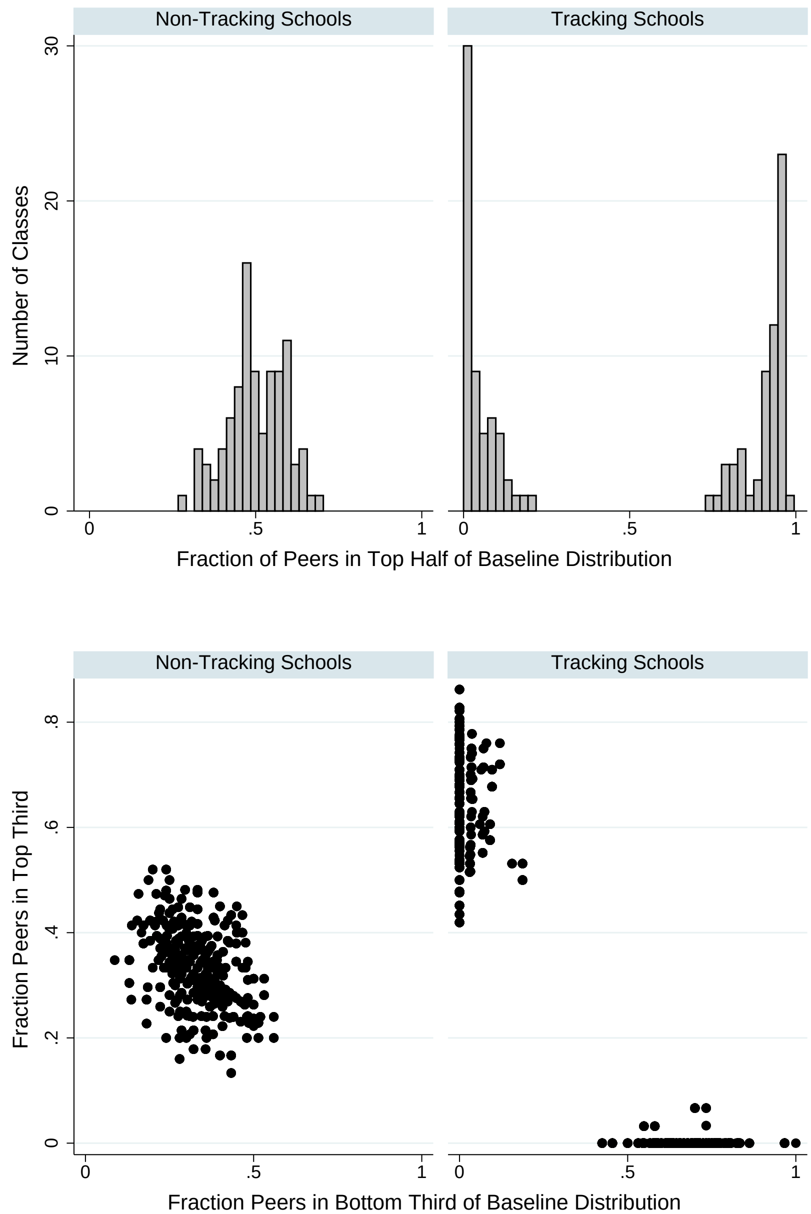


Figure 3.2: Change in class composition induced by the experiment. Summary statistics are for 48 non-tracking and 60 tracking schools for which baseline test score is nonmissing.

3.2.2 Experimental Results

Table 3.2 reproduces the main results of Duflo et al. (2011) measuring the impact of tracking on students' endline test scores. The baseline specification is

$$Y_i = \beta_0 + \beta_1 \cdot T_i + X_i' \cdot \beta + \nu_i$$

where Y_i is endline test score, $T_i = 1$ if student i is in a tracking school, and X_i are baseline test score percentile, age, and gender. Estimates are reported in Column 2. Controlling for pretreatment characteristics, students in tracking schools exhibit endline test scores that are on average 0.17 standard deviations higher than students in control schools, which is statistically significant from zero at 1%. Column 3 allows for heterogeneous treatment effects by whether the student was above or below the median baseline score in her school. I estimate the specification

$$Y_i = \alpha_0 + \alpha_1 \cdot T_i + \alpha_2 \cdot b_i + \alpha_3 \cdot T_i \cdot b_i + X_i' \cdot \alpha + \epsilon_i$$

where $b_i = 1$ if the student was above her school's median baseline test score. Students both above and below the baseline median show statistically significantly higher endline test scores in tracking schools (0.15 standard deviation gain for students in the bottom half and 0.18 standard deviation gain for students in the top) and I cannot reject that the magnitude of the effect is the same for students above and below the baseline median. Table 3 of Duflo et al. (2011) (not replicated here) tests for heterogeneity in the impact of tracking by other demographics including age and gender; they find limited statistical evidence for heterogeneity in treatment effects.

Table 3.2: Overall Effect of Tracking in Experimental Data

	Endline Test Score		
	(1)	(2)	(3)
Tracking School	0.14*	0.17***	0.15**
	(0.07)	(0.06)	(0.07)
Tracking School			0.03
x Top Half Initial Distribution			(0.10)
Individual Controls	No	Yes	Yes
F Test: Coeff (Tracking Variables) = 0			3.85**
p value			0.02
F Test: Coeff (Bottom) = Coeff (Top)			0.10
p value			0.75
Number of Observations	5795	5269	5135
Adjusted R^2	0.01	0.24	0.25

This table replicates portions of Duflo et al. (2011), Table 2a. Significant at: * 10%; ** 5%; *** 1%. Dependent variable is endline test score, rescaled to have zero mean and unit variance in the non-tracking sample. Controls not reported are baseline test score percentile, age at endline, and gender. Regression 3 include a dummy for being above the school baseline median score. Ordinary least squares standard errors clustered by school are included in parentheses.

3.3 Peer Effects Framework

In this section I present a simple conceptual framework based on Graham et al. (2010) which nests most models of peer effects in the literature. Consider a population of students, indexed by i, each with a vector of observable characteristics X_i drawn from population distribution f_X. The students are randomly assigned to class groups of size N and classes are randomly assigned to facilities conditional on some subset $\hat{X}$ of X, thus satisfying a conditional version of double randomization (Graham 2008). I observe M randomly-selected classes and an outcome Y_i for each student after participation in her assigned class.[2]

I assume that the production function can be written as

$$Y_i = g(X_i) + h(Z_i, F_{Z_{-i}}) + \epsilon_i$$

where $E(Y_i|X = X_i) = g(X_i)$ is student i's expected outcome given her own observables and the conditional double randomization assignment above, Z is some subset of the observables X, $F_{Z_{-i}}$ is the empirical distribution of the Z of $i's$ classmates, and $E(h(Z_i, F_{Z_{-i}})|X_i) = 0$. The function $h(Z_i, F_{Z_{-i}})$ is the *peer effects production function*. It is the difference between $i's$ expected outcome given peer distribution $F_{Z_{-i}}$ and her expected outcome given a class randomly drawn from f_x conditioning on $\hat{X}$. I make no a priori assumptions about the form of h except that the peer effects are *distributional* (Manski, 2011): any impact of peer group composition, including both direct and indirect effects, operates through the distribution of Z_{-i}. Implicit in this specification is that peers are exchangeable conditional on Z. For further discussion of the assumptions underlying this specification, see Appendix C.1.

The variables Z can be thought of as the subset of variables that the researcher believes impact the achievement of a student's peers. For example, if X includes both academic and demographic variables, Z may be only the academic variables, or Z may be a subset of both demographic and academic variables. In relatively small peer groups the use of Z_{-i} excluding i may induce a mechanical negative bias in estimates; see Lyle (2007).

Following Table 4 of Duflo et al. (2011), I assume that g is linear and that Z is the baseline test score. I can thus write the outcome as

$$Y_i = \beta_0 + X_i' \cdot \beta + h(Z_i, F_{Z_{-i}}) + \eta_s + \epsilon_i$$

[2] In my data classes are sampled in pairs, which impacts my cross-validation procedure but makes no difference for my estimates.

where X_i consists of own baseline score, age, and gender, and η_s is a set of school fixed effects. Note that this framework nests that of Duflo et al. (2011) if I assume all teachers exert the same level of effort, as I can set h to be equal to the sum of the direct and indirect peer effects.

Even though Z consists of a single variable, with limited data and peer groups of moderate size, nonparametric estimation of h is infeasible. I thus consider combinations of functional form assumptions and summary statistics for $F_{Z_{-i}}$ that allow for estimation of h.

3.4 Nonparametric Estimates of the Peer Effects Production Function

To isolate the role that summary statistic selection plays in correctly estimating $h(Z_i, F_{Z_{-i}})$, I use nonparametric regression to estimate $h(Z_i, F_{Z_{-i}})$ using several different sets of summary statistics for $F_{Z_{-i}}$. I first estimate the expectation of Y_i given own characteristics

$$E(Y_i|X_i, s_i) = \beta_0 + X_i' \cdot \beta + \eta_s$$

on the control group data and compute the residual $\widehat{R_i} = Y_i - \widehat{\beta_0} - X_i' \cdot \widehat{\beta} - \widehat{\eta_s}$. Figure 3.3 plots the local linear regression of $\widehat{R_i}$ on the mean and standard deviation of peer baseline score for students below (left) and above (right) the median of the baseline score. Details of the estimation procedure are given in Appendix C.2. I can immediately see that the outcomes of both low and high ability students are monotonically increasing in mean peer ability, while standard deviation has little effect. This simple plot leads to a striking conclusion: a model using the mean and standard deviation of peer baseline scores as summary statistics for $F_{Z_{-i}}$ would predict large losses from tracking for students in the bottom half of the baseline distribution, in contrast to the experimental result that tracking improved outcomes for bottom students.

Figure 3.4 plots $\widehat{R_i}$ as a function of the median and interquartile range of peer baseline scores. While peer median has little impact on outcomes, outcomes are decreasing in peer baseline interquartile range for both low and high ability students. This is consistent with the experimetal

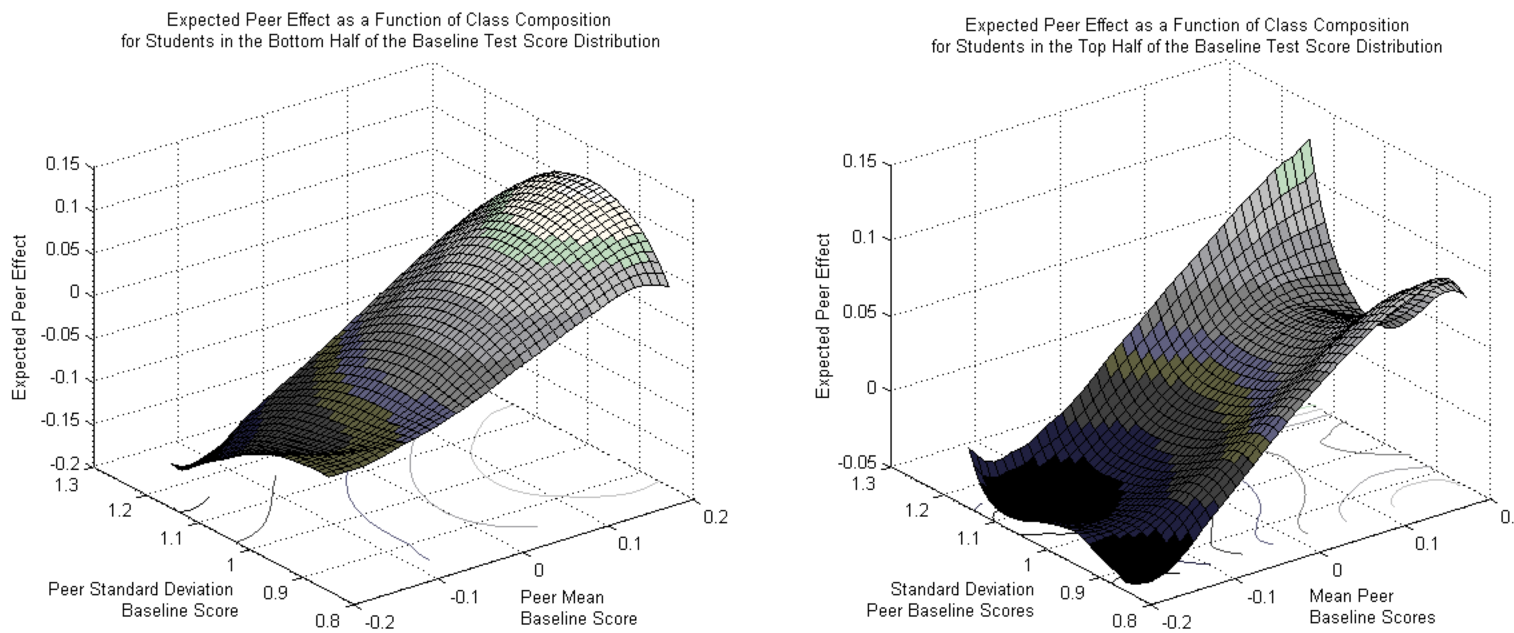


Figure 3.3: Nonparametric estimates of the peer effects production function using the mean and standard deviation of peer baseline scores. See text and Appendix C.2 for estimation procedure. Estimates are for 48 non-tracking and 60 tracking schools for which baseline test score is nonmissing.

finding that tracking schools, which have more homogenous classes, have higher endline test scores on average for all students.

Figures 3.5 and 3.6 model $\widehat{R}_i$ as a function of the share of peers in quantiles of the baseline ability distribution. Predictions from these models are inconsistent: while the estimates using the fraction peers above the median produces estimates of plausible sign for the top students, they indicate peer group composition has little effect on outcomes of bottom students. Estimates using fraction peers in the top and bottom third of the baseline distribution indicate that tracking would decrease the outcomes of all students.

3.5 Parametric Models of Peer Effects

I next estimate a series of flexible linear models using the summary statistics discussed in the previous section and the data from the control schools. These parametric specifications are easier to compute than the nonparametric estimates in the previous sections and allow easy comparisons of in sample fit and out of sample predictive accuracy.

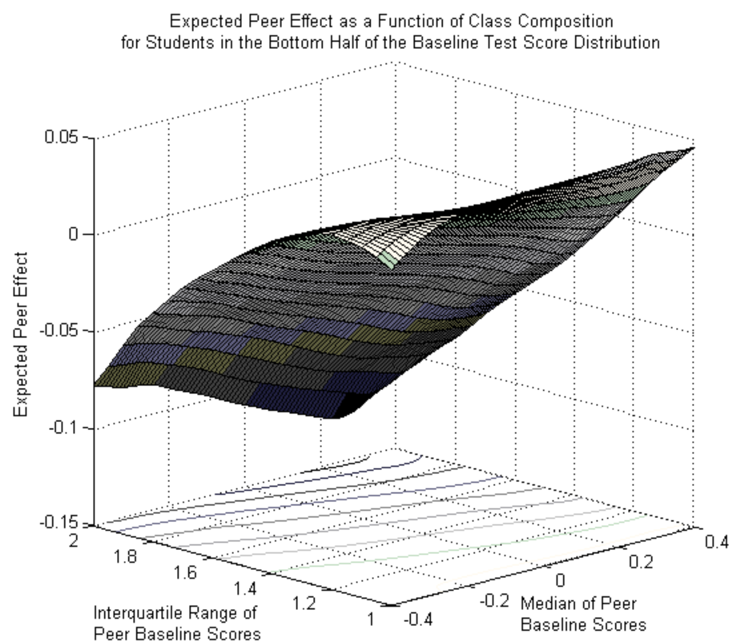
3.5.1 Moment-Based Models

Table 3.3 reports estimates of moment-based models. my baseline specification is the canonical linear-in-means model (Manski, 1993; Duflo et al., 2011, Table 4)

$$Y_i = \beta_0 + \beta_1 \cdot \overline{Z_{-i}} + X_i \cdot \beta + \eta_s + \epsilon_i$$

where $\overline{Z_{-i}}$ is the mean baseline test score for the classmates of individual i, X_i is own baseline, age, and gender, and η_s is a school dummy. Estimates are given in Column 1. A one standard deviation increase in peer mean ability increases expected endline test score by 0.04 standard deviations, which is significant at 5%.

Column 2 interacts peer mean baseline score with whether the student was above or below the baseline median score. The coefficient on mean peer baseline score is larger for students in



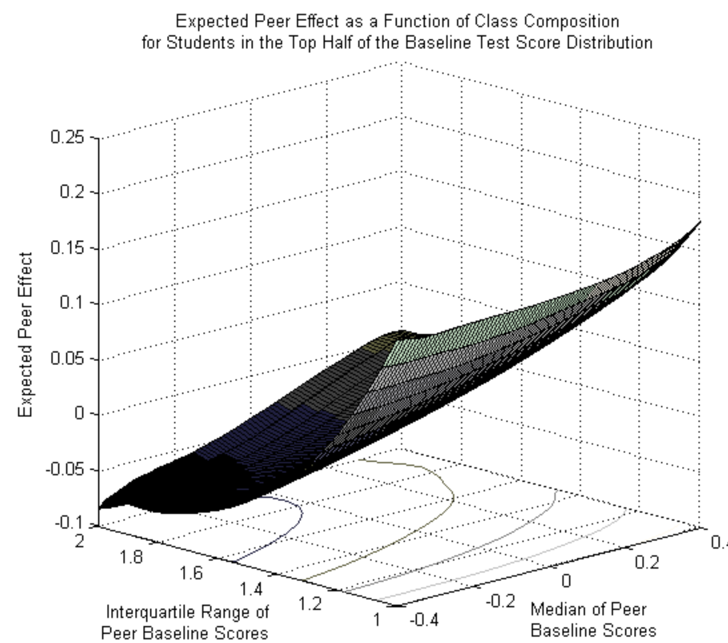


Figure 3.4: Nonparametric estimates of the peer effects production function using the median and interquartile range of peer baseline scores. See text and Appendix C.2 for estimation procedure. Estimates are for 48 non-tracking and 60 tracking schools for which baseline test score is nonmissing.

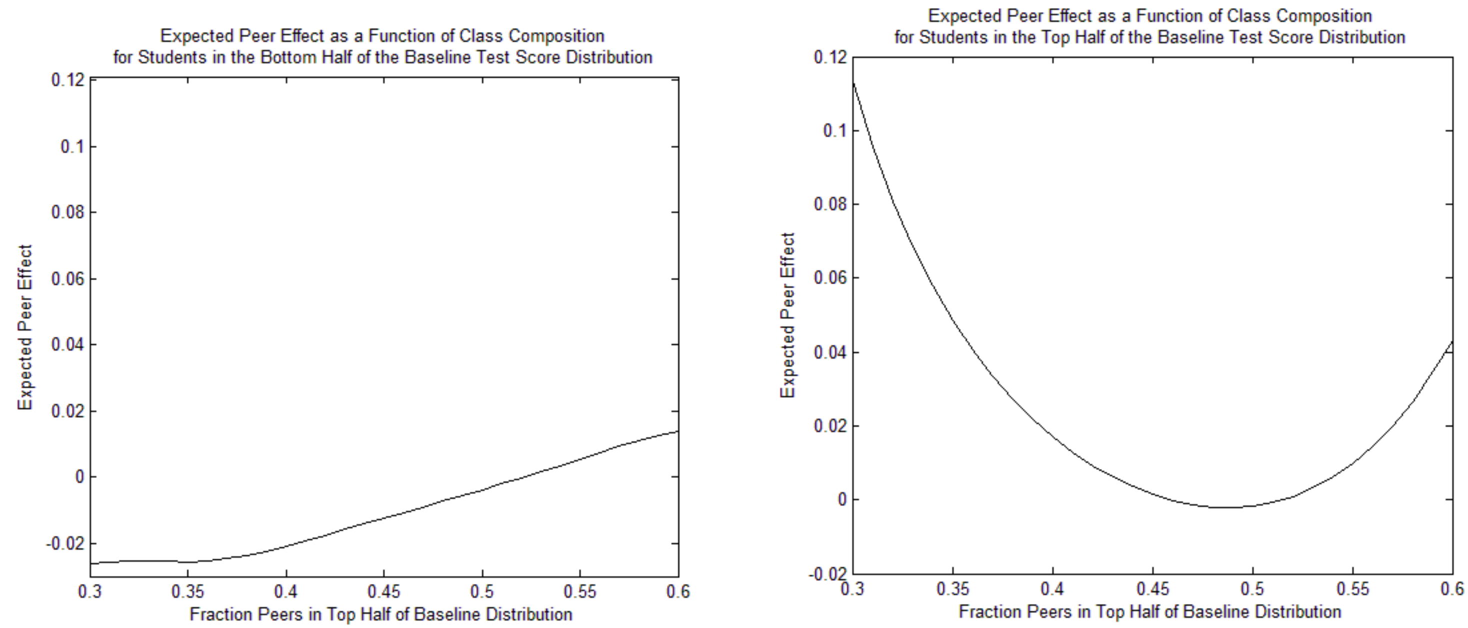


Figure 3.5: Nonparametric estimates of the peer effects production function using the the fraction of peers in the top half of the baseline ability distribution. See text and Appendix C.2 for estimation procedure. Estimates are for 48 non-tracking and 60 tracking schools for which baseline test score is nonmissing.

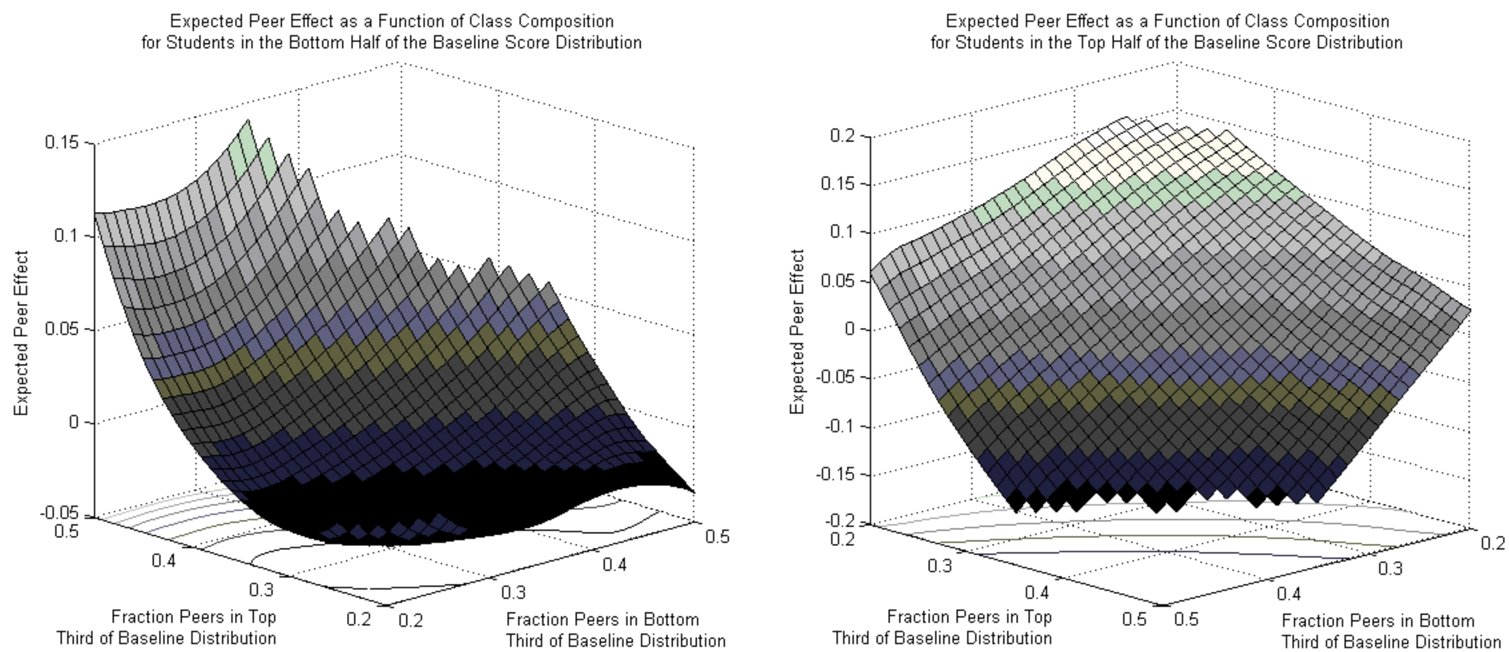


Figure 3.6: Nonparametric estimates of the peer effects production function using the the fraction of peers in the bottom and top third of the baseline ability distribution. See text and Appendix C.2 for estimation procedure. Estimates are for 48 non-tracking and 60 tracking schools for which baseline test score is nonmissing.

the bottom half of the ability distribution and is significant at 5%. Peer standard deviation is not statistically significant (Columns 3 and 4) and does not alter the coefficient or significance of peer mean. Adding higher order terms (Columns 5 and 6) renders the peer group composition variables individually and jointly not statistically significant.

The persistent positive and significant coefficient on peer mean baseline score in models without higher order terms confirms the conclusion from the nonparametric estimates that a model including peer mean baseline score unambiguously predicts losses from tracking for bottom students. I address formal prediction of treatment effects in the next section.

3.5.2 Share-Based Models

Share-based models are frequently used to avoid parametric assumptions about the peer effects production function and to detect nonlinearities (Sacerdote 2001; Hoxby and Weingarth 2006; Carrell et al. 2011). Let $b_i = 1$ if student i's baseline score was above the median of the baseline ability distrbution, $t_{1i} = 1$ if i was in the bottom third, and $t_{3i} = 1$ if i was in the top third. Column 1 of Table 3.4 reports estimates of the model

$$Y_i = \beta_0 + \beta_1 \cdot \overline{b_{-i}} + \beta_2 \cdot \left(\overline{b_{-i}}\right)^2 + X_i' \cdot \beta + \eta_s + \epsilon_i$$

where again X_i is baseline score, age, and gender.[3] β_1 and β_2 are individually and jointly statistically significant at 5%. Including interaction terms between student above/below the baseline median and the peer composition variables (Column 2) confirms the findings of the nonparametric estimates that high ability students significantly benefit from more homogenous peer groups while bottom students show no response to peer group composition.

Columns 3 through 6 use fraction peers in the top and bottom third of the baseline distribution to characterize the peer ability distribution. Column 3 gives estimates of the baseline specification

[3] In models omitting the squared peer variable, fraction peers above the median is not statistically significant for any baseline ability. I omit this specification to save space.

Table 3.3: Moment-Based Models of Peer Effects

	Endline Test Score								
Peer Baseline Scores	(1)	(2)		(3)	(4)		(5)	(6)	
	All	Below	Above	All	Below	Above	All	Below	Above
Mean	0.37**	0.49**	0.27	0.37**	0.49**	0.28	-4.70	-7.15	-8.20
	(0.17)	(0.22)	(0.24)	(0.17)	(0.23)	(0.25)	(7.11)	(7.84)	(8.52)
Standard Deviation				0.06	-0.03	0.13	10.80	14.45	4.18
				(0.19)	(0.28)	(0.35)	(14.26)	(14.63)	(15.95)
Mean^2							-0.35	-4.99	-5.26
							(4.27)	(5.85)	(5.45)
Standard Deviation^2							-5.41	-7.38	-1.96
							(7.20)	(7.37)	(8.08)
Mean x Standard Deviation							5.13	7.90	8.43
							(7.17)	(7.93)	(8.66)
F Tests									
Coeff (Peer Variables) = 0		2.85*		2.48*	1.50		1.19	1.05	
p value		0.06		0.09	0.20		0.32	0.41	
Coeff (Below) = Coeff (Above)		0.61			0.45			0.75	
p value		0.54			0.72			0.61	
Coeff(Higher Order Terms)=0							0.52	0.95	
p value							0.67	0.46	
Number of Observations	2179	2179		2179	2179		2179	2179	
Adjusted R^2	0.37	0.37		0.37	0.37		0.37	0.37	

Column 1 replicates Duflo et al. (2011), Table 4a, Column 1. Significant at: * 10%; ** 5%; *** 1%. Sample is 48 schools with randomly-assigned classes and nonmissing baseline scores. "Below" denotes students below the median baseline test score and "Above" denotes students above. Dependent variable is endline test score, rescaled to have zero mean and unit variance. All regressions include own baseline score, age at endline, gender, and school fixed effects. Even-numbered regressions include a dummy for baseline score below the median. Standard errors clustered by class are included in parentheses.

Table 3.4: Share-Based Models of Peer Effects

	Endline Test Score								
Peer Baseline Scores	(1)	(2)		(3)	(4)		(5)	(6)	
	All	Below	Above	All	Below	Above	All	Below	Above
Fraction Above Median	-7.58**	-3.91	-12.26***						
	(2.93)	(3.08)	(3.73)						
Fraction Above Median^2	7.55**	3.95	12.42***						
	(2.96)	(3.09)	(3.88)						
Fraction Bottom Third				-0.74**	-0.24	-1.25	-1.78	-5.28	0.68
				(0.30)	(0.40)	(0.41)	(2.31)	(3.52)	(3.29)
Fraction Top Third				-0.61*	0.14	-1.34	-6.55**	-8.86**	-2.42
				(0.36)	(0.47)	(0.51)	(2.66)	(3.95)	(4.62)
Fraction Bottom Third^2							1.21	4.16	-0.27
							(2.59)	(3.48)	(3.05)
Fraction Top Third^2							8.53***	9.90**	4.43
							(3.22)	(4.26)	(5.11)
Fraction Bottom x Fraction Top							0.94	7.00	-5.26
							(3.92)	(5.84)	(6.49)
F Tests									
Coeff(Peer Variables) = 0	3.39**	2.86**		3.63**	3.25**		3.02**	1.94**	
p value	0.04	(0.03)		(0.03)	(0.02)		(0.01)	(0.05)	
Coeff(Below) = Coeff(Above)		2.39*			2.08			1.08	
p value		(0.07)			(0.11)			(0.38)	
Coeff(Higher Order Terms) = 0		5.30***					2.53*	1.25	
p value		(0.01)					(0.06)	(0.29)	
Number of Observations	2179	2179		2179	2179		2179	2179	
Adjusted R^2	0.37	0.37		0.37	0.37		0.37	0.37	

Significant at: * 10%; ** 5%; *** 1%. Sample is 48 schools with randomly-assigned classes and nonmissing baseline scores. "Below" denotes students with baseline scores below the median and "Above" above the median. Dependent variable is endline test score, rescaled to have zero mean and unit variance. All regressions include own baseline score, age at endline, gender, and school fixed effects. Even numbered regressions include a dummy for initial score above the median. Standard errors clustered by class are included in parentheses.

$$Y_i = \beta_0 + \beta_1 \cdot \overline{t_{1,-i}} + \beta_2 \cdot \overline{t_{3,-i}} + X_i' \cdot \beta + \eta_s + \epsilon_i$$

Both peer variables are weakly significant with negative coefficients. Adding higher order terms and below/above the median interactions, the most striking finon outcomes ding is that increasing the fraction of peers in the top third of the baseline distribution appears to have a significant positive effect on all students and, in particular, students below the median. This again contradicts the experimental evidence discussed earlier as well as the estimates in Columns 1 and 2.

3.5.3 Quartile-Based Models

Finally, I estimate models using quartiles of the peer baseline score distribution. Table 3.5, Columns 1 and 2 report regressions using the median peer baseline score only. The median is not statistically significant. Column 3 reports

$$Y_i = \beta_0 + \beta_1 \cdot \mu_{1/2}(Z_{-i}) + \beta_2 \cdot (\mu_{3/4}(Z_{-i}) - \mu_{1/4}(Z_{-i})) + X_i' \cdot \beta + \eta_s + \epsilon_i$$

where $\mu_{1/2}(Z_{-i})$ is the median of Z_{-i} and $\mu_{3/4}(Z_{-i})$ and $\mu_{1/4}(Z_{-i})$ are the upper and lower quartiles, respectively. While the median is still not statistically significant, the coefficient on interquartile range is negative, large, and statistically significant at 1%. A one standard deviation increase in interquartile range implies a 0.09 standard-deviation decrease in endline test score. Column 4 interacts the peer group composition variables with above/below the baseline median indicators; the coefficient on interquartile range is negative and statistically significant for both bottom and top students, and I cannot reject that the coefficients are equal. Estimates in Column 5 and 6 including higher order terms and interactions suggest that the relationship between interquartile range and outcome may be quadratic.

Together, the estimates from linear models suggest that both summary statistic selection and functional form assumptions influence whether a researcher would find statistically significant peer

Table 3.5: Quartile-Based Models of Peer Effects

	Endline Test Score								
Peer Baseline Scores	(1)	(2)		(3)	(4)		(5)	(6)	
	All	Below	Above	All	Below	Above	All	Below	Above
Median	0.03	-0.00	0.07	0.01	-0.05	0.06	-0.40	-0.36	-0.28
	(0.11)	(0.12)	(0.16)	(0.10)	(0.12)	(0.15)	(0.43)	(0.49)	(0.67)
Interquartile Range				-0.29***	-0.25***	-0.34***	-1.28***	-0.61	-2.04***
				(0.08)	(0.10)	(0.11)	(0.42)	(0.51)	(0.68)
Median^2							0.27	0.30	0.41
							(0.33)	(0.41)	(0.41)
Interquartile Range^2							0.34***	0.12	0.59**
							(0.14)	(0.18)	(0.23)
Median x Interquartile Range							0.28	0.20	0.26
							(0.30)	(0.35)	(0.47)
F Tests									
Coeff (Peer Variables) = 0		0.12		6.50***	3.38**		4.40***	2.26**	
p value		0.89		0.002	0.01		0.001	0.02	
Coeff (Below) = Coeff (Above)		0.41			0.39			1.04	
p value		0.67			0.76			0.40	
Coeff(Higher Order Terms) = 0							2.93**	1.79	
p value							0.04	0.11	
Number of Observations	2179	2179		2179	2179		2179	2179	
Adjusted R^2	0.37	0.37		0.37	0.37		0.37	0.37	

Significant at: * 10%; ** 5%; *** 1%. Sample is 48 schools with randomly-assigned classes and nonmissing baseline scores. “Below” denotes students with baseline scores below the median and “Above” students above. Dependent variable is endline test score, rescaled to have zero mean and unit variance. All regressions include own baseline score, age at endline, gender, and school fixed effects. Even numbered regressions include a dummy for baseline score above the median. Standard errors clustered by class are included in parentheses.

effects in this data. I now use the outcomes from the tracking schools to compare the predictive accuracy of these models.

3.6 Measuring Fit

3.6.1 Predicted Treatment Effects and Prediction Error

I use the estimates from Tables 3.3 through 3.5 to predict the net impact on endline test scores of switching from randomly-assigned to tracked classes. This is a particularly demanding challenge for the models since they will be predicting outcomes for class compositions outside the domain on which they were estimated.

Recall that I assume the expectation of the outcome Y is given by

$$E(Y_i|X_i, F_{Z_{-i}}, s_i) = \beta_0 + X_i' \cdot \beta + h(Z_i, F_{Z_{-i}}) + \eta_s$$

I consider the counterfactual in which each school with randomly-assigned classes is reorganized so that students above the median ability are in one class and below the median are in the other. Given the baseline ability distribution in each school, it is straightforward to compute the class summary statistics for these counterfactual "treatment" schools. Let $\bar{F}_{Z_{-i}}$ be the distribution of $i's$ hypothetical classmates' characteristics resulting from this reassignment. The expected gains for a student with characteristics X in school s switching from randomly assigned classes to tracked classes is thus

$$E(Y_i|X_i, s_i, T_i = 1) - E(Y_i|X_i, s_i, T_i = 0)$$

$$= E[h(Z_i \bar{F}_{Z_{-i}})|X_i, s_i, T_i = 1] - E[h(Z_i, F_{Z_{-i}})|X_i, s_i, T_i = 0]$$

Since all peer variables either have pooled coefficients or are interacted only with own position above or below baseline median and Z is standardized within school, I can simplify this to

$$E[h(b_i, \bar{F}_{Z_{-i}})|b_i, T_i = 1] - E[h(b_i, F_{Z_{-i}})|b_i, T_i = 0]$$

Because schools are randomly chosen to have randomly assigned or tracked classes, this is straightforward to estimate from sample means using an estimate of $h(b_i, F_{Z_{-i}})$ from the control group data and the class compositions in the tracking and control schools. Standard errors are computed using the Delta method.

Table 3.6 reports predicted treatment effects for the eighteen models in Tables 3.3 through 3.5. The experimental gains from tracking are included at the bottom of the table for comparison. It is easy to see that the models provide very different estimates of the impact of tracking on outcomes. Of models without higher order terms, almost every moment-based model predicts large, statistically significant losses from tracking for bottom students. The predictions of models using the fraction of peers above the median have the correct sign and significance; however, the predictions are an order of magnitude too large. The other shares-based models, using fraction in the top and bottom third, report either no or only a weakly statistically significant effect of switching class assignment regimes. The models that produce estimates that most closely match the experimental estimates are models including median and interquartile range. Models including higher order terms and interactions give predictions with very large standard errors so estimates are either not statistically different from zero or are far too large.

Table 3.7 reports the root mean squared prediction error for each model in Tables 3.3 through 3.5. The prediction error is computed by estimating the models on the control data and predicting the outcomes in the treatment schools. Again the models vary widely in their predictive accuracy. Models using the median and interquartile range without higher order terms have the lowest prediction error, while models with higher order terms have large errors, most likely due to overfitting.

3.6.2 Model Selection Criteria

While the experimental data allows us to measure the predictive ability of the estimated models, I may wish to ask whether I could have determined the best model using only the data from the control schools. In Table 3.7 I report the Bayesian information criterion (BIC) and the root mean

Table 3.6: Predicted Treatment Effects Using Econometric Models

		Pooled			By Below/Above Median		
		Below	Above	All	Below	Above	All
Moment-Based	Mean	-0.26**	0.28**	0.01**	-0.34**	0.20	-0.07
Models		(0.12)	(0.13)	(0.00)	(0.16)	(0.18)	(0.12)
	Mean, SD	-0.29*	0.26*	-0.02	-0.32*	0.16	-0.09
		(0.15)	(0.15)	(0.08)	(0.19)	(0.19)	(0.13)
	Higher Order Terms	0.00	-1.93	-0.95	-2.53	-5.73	-4.10
		(4.33)	(2.70)	(2.81)	(5.09)	(3.78)	(3.60)
Share-Based	Fraction Above Median,	1.54***	1.36**	1.45**	0.81	2.32***	1.55**
Models	Above Median^2	(0.59)	(0.57)	(0.57)	(0.63)	(0.78)	(0.62)
	Fraction Bottom Third,	-0.05	0.04	-0.01*	-0.11	-0.03	-0.07
	Top Third	(0.12)	(0.12)	(0.003)	(0.13)	(0.16)	(0.08)
	Higher Order Terms	0.88	0.93*	0.91*	0.67	0.95	0.81
		(0.54)	(0.48)	(0.50)	(0.63)	(0.67)	(0.54)
Quartile-Based	Median	-0.02	0.02	0.00	0.00	0.05	0.03
Models		(0.07)	(0.08)	(0.00)	(0.08)	(0.11)	(0.06)
	Median, IQR	0.19**	0.17**	0.18***	0.20**	0.23*	0.21***
		(0.09)	(0.08)	(0.05)	(0.09)	(0.12)	(0.08)
	Higher Order Terms	0.61**	0.28	0.45**	0.53**	0.51	0.52**
		(0.24)	(0.21)	(0.18)	(0.26)	(0.33)	(0.21)
Experimental Estimates		0.15**	0.18**	0.17***			
		(0.07)	(0.09)	(0.06)			

Significant at: * 10%; ** 5%; *** 1%. Predicted treatment effects computed for models estimated in Tables 3-5. Each cell is the average predicted endline score in the tracking peer group assignment minus the average expected endline score in the control assignment. "Pooled" indicates homogenous coefficients on peer variables. "By Below/Above Median" indicates peer variables are interacted with student below/above baseline median. "Below" indicates students below baseline median and "Above" indicates above. Standard errors in parentheses computed using the Delta method.

Table 3.7: Measures of Model Fit

		BIC		Cross-Validation RMSE		Prediction RMSE	
		Pooled	By Below/ Above Median	Pooled	By Below/ Above Median	Pooled	By Below/ Above Median
Moment-Based Models	Mean	5163.9	5178.3	0.8793	0.8792	0.94	0.96
	Mean, SD	5171.5	5193.5	0.8799	0.8804	0.95	0.96
	Higher Order Terms	5193.3	5234.4	0.8803	0.8886	1.97	4.84
Share-Based Models	Fraction Above Median, Above Median^2	5167.4	5184.2	0.8828	0.8817	1.61	1.87
	Fraction Bottom Third, Top Third	5171.5	5184.4	0.8800	<u>0.8779</u>	0.90	0.92
	Higher Order Terms	5188.5	5222.9	0.8836	0.8824	1.20	1.13
Quartile-Based Models	Median	5169.3	5184.0	0.8801	0.8803	<u>0.89</u>	<u>0.89</u>
	Median, IQR	<u>5161.3</u>	5182.9	0.8827	0.8831	<u>0.89</u>	<u>0.89</u>
	Higher Order Terms	5178.8	5220.0	0.8873	0.8890	0.98	0.99

Statistics are for estimates reported in Tables 3.3-3.5. The best (smallest) score for each measure of fit is underlined. "Pooled" indicates homogeneous coefficients for peer variables. "By Below/Above Median" indicates that peer variables are interacted with dummies for student below/above baseline median score. "BIC" is the Bayesian information criterion for estimates using the control group data. "Cross-Validation RMSE" is the root mean squared error for leave-one-school-out cross-validation, estimated on the control schools. "Prediction RMSE" is the root mean squared prediction error for the tracking school outcomes using estimates from control school data.

squared error for leave-one-school-out cross-validation, for the control group estimates. Cross-validation is performed by estimating each model on data from 47 control schools and using the estimates to predict outcomes for the omitted school. This is repeated leaving each school out once.

I see that the choice of model selection criterion has some impact on whether the most accurate model is chosen. The pooled median-interquartile range model, which had the predictions closest to the experimental estimates and the lowest prediction RMSE, has the lowest BIC value. The Akaike information criterion (not reported) selects this model as well. However, cross-validation selects models that have very poor predictive power: the model with the lowest cross-validation RMSE is the shares model with interactions which predicts that tracking has no impact on outcomes, followed by the model using the mean which predicts losses from tracking for bottom students.

3.7 Sensitivity Analysis

Using the mean and standard deviation to describe peer group composition assumes that peer characteristics are normally distributed; in a relatively small group such as a classroom, this assumption can easily be violated. Here, I investigate the sensitivity of peer effects estimates to changes in the measures of mean and dispersion used in the model.

In Table 3.8 I use differences in peer score deciles to systematically vary the fraction of peers included in the measure of peer group dispersion. I estimate models of the form

$$Y_i = \beta_0 + \beta_1 \cdot \mu_{1/2}(Z_{-i}) + \beta_2 \cdot (\mu_{(5+k)/10}(Z_{-i}) - \mu_{(5-k)/10}(Z_{-i})) + X_i' \cdot \beta + \eta_s + \epsilon_i$$

using the control school data, where $\mu_{1/2}(Z_{-i})$ is the median of peer baseline scores, $\mu_{j/10}(Z_{-i})$ is the j^{th} decile of $i's$ peer baseline scores, and $k = \{1, \ldots 5\}$. As k increases, a higher fraction of peers are included in the dispersion measure and outliers should have a larger impact.

Table 3.8: Models Using Alternate Measures of Peer Ability Dispersion

		Endline Test Score				
Peer Baseline Scores		(1)	(2)	(3)	(4)	(5)
Median		0.04	0.03	0.01	0.02	0.03
		(0.11)	(0.10)	(0.09)	(0.11)	(0.11)
60th - 40th percentiles		-0.25**				
		0.10				
70th - 30th percentiles			-0.27***			
			(0.08)			
80th - 20th percentiles				-0.32***		
				(0.08)		
90th - 10th percentiles					-0.14*	
					(0.08)	
Range						0.09**
						(0.04)
F Test: Coeff (Peer Vars.) = 0		3.18**	6.19***	9.01***	1.82	2.99*
p value		0.05	0.00	0.00	0.17	0.06
BIC		5172.1	5165.3	<u>5153.1</u>	5172.1	5172.8
Cross-Validation RMSE		0.8799	<u>0.8780</u>	0.8826	0.8835	0.8810
Prediction RMSE		0.89	<u>0.88</u>	0.89	<u>0.88</u>	0.93
Predicted Treatment	All	0.05**	0.13***	0.26***	0.17*	-0.13**
Effects		(0.02)	(0.04)	(0.06)	(0.09)	(0.05)
	Above	0.07	0.14*	0.23***	0.16	-0.07
		(0.08)	(0.08)	(0.08)	(0.10)	(0.09)
	Below	0.03	0.13*	0.28***	0.17	-0.19**
		(0.07)	(0.08)	(0.09)	(0.13)	(0.10)
Number of Observations		2179	2179	2179	2179	2179
Adjusted R^2		0.37	0.37	0.37	0.37	0.37

Significant at: * 10%; ** 5%; *** 1%. The best (smallest) score for each measure of fit is underlined. Sample is 48 schools with randomly-assigned classes and nonmissing baseline scores. Dependent variable is endline test score, rescaled to have zero mean and unit variance. All regressions include own baseline score, age at endline, gender, and school fixed effects. Standard errors clustered by class are included in parentheses. For details on computing predicted treatment effects, see Table 3.6. For details on computing measures of model fit, see Table 3.7.

The 70-30 and 80-20 measures of dispersion provide the best estimates of the peer effects production function. The coefficient on the dispersion measure is highly significant and the estimates of gains from tracking are of the correct sign, appropriate magnitude, and are statistically significant. Using the 70th and 30th or 90th and 10th deciles produces the smallest prediction RMSE, while estimates using the 80th and 20th percentiles have the lowest BIC and predict gains from tracking that are statistically significant at 1%.

As the fraction of data in the dispersion measure increases, however, the predictive accuracy of the models decreases. Using the 90-10 range predicts overall gains from tracking that are barely significant at 10%, while the model using the range predicts statistically significant losses from tracking for all students. The coefficient on the range is significant at 5% but of the wrong sign.

Together, these estimates demonstrate the sensitivity of peer effects predictions to the exact specification chosen for estimation. Both model selection criteria would have chosen models with decent predictive accuracy from this set; however, arbitrarily choosing a specification without using model selection criteria could easily result in estimates of the wrong sign.

3.8 Conclusion

I use the experimental data of Duflo et al. (2011) to test the ability of popular reduced-form models of peer effects to predict the impact of peer group reassignment on outcomes. I find that both the choice of summary statistics for peer group composition and functional form assumptions are important for the detection of peer effects and out of sample predictive accuracy of estimates. Using moments as summary statistics for peer group composition leads to incorrect predictions of the impact of tracking on outcomes, while specifications using robust descriptive statistics such as the median and interquartile range perform more reliably. Seemingly arbitrary changes in the summary statistics used to describe class composition result in peer effects estimates of opposite sign. Likelihood-based model selection criteria provide some suggestive ex-post guidance on the most accurate model.

While no peer effects specification will be universally superior for all applications, the wide range of counterfactual estimates produced by popular peer effects specifications in this setting is alarming to the applied researcher. The development of flexible reduced-form peer effects specifications as well as tests for selecting among specifications in different empirical contexts is a topic that deserves further study in the agenda of reconciling the theoretical and empirical peer effects literatures.

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Appendix A

Appendix to Chapter 1

A.1 Proof of Proposition 1

The proof is standard in the literature Browning et al. (2011). Each agent's utility is $u_i(c_i, e, 1_K) = c_i \cdot G(e + \gamma \cdot 1_K)$ and the total utility of a couple with income y is $\eta_{ij}(y, 1_K) = \max_e (y - e) \cdot G(e + \gamma \cdot 1_K)$. By the envelope theorem $\frac{\partial \eta_{ij}}{\partial y} = G(q^*(y))$. Since $q^*(y)$ is increasing in y and G is increasing in q, $\eta_{ij}(y + \gamma \cdot 1_K)$ is convex in y.

A.2 Proofs for Section 1.4

Let subscript H denote an individual in occupation Hi and L denote an individual in occupation Lo. Hi marry Hi if and only if

$$\eta_{HH} + \eta_{LL} \geq \eta_{HL} + \eta_{LH} \tag{A.1}$$

For a couple consisting of man with wage w_i and woman with wage w_j, re-write their marital surplus as $f(y_{ij})$ where $y_{HH} = \max\{w_{2f}(1-\tau) + w_{2m} + \gamma, w_{2f} + w_{2m}\}$, $y_{LH} = \max\{w_{2f} + w_1(1 - \frac{\tau}{\alpha}) + \gamma, w_{2f}(1-\tau) + w_1 + \gamma, w_{2f} + w_1\}$, $y_{HL} = w_{2m} + w_1(1-\tau) + \gamma$, and $y_{LL} = w_1(2-\tau) + \gamma$.

A.2.1 Proof of Lemma 1

Equation A.1 can be rewritten as $f(\hat{w_{2f}} + w_{2m}) - f(\hat{w_{2f}} + w_1) \geq f(\hat{w}_1 + w_{2m}) - f(w_1 + \hat{w}_1)$ where $\hat{w}_i = \max\{w_i(1-\tau) + \gamma, w_i\}$. Since $\hat{w_{2f}} \geq \hat{w}_1$, this holds by the convexity of f.

A.2.2 Proof of Theorem 1

When men Lo have comparative advantage in home production when married to women in occupation Hi, there is a continuous cutoff function $\hat{\alpha}(\tau)$ such that for $\alpha > \hat{\alpha}$, negative assortative matching on occupation is stable and for $\alpha \leq \hat{\alpha}$, positive assortative matching is stable.

The condition for positive assortative matching can be rewritten as $f(y_{LH}) \leq \eta_{HH} - (\eta_{HL} - \eta_{LL})$. Fixing τ, the right hand side of this inequality is constant. When men in occupation Lo provide childcare, y_{LH}, and thus the left hand side, is continuous and strictly increasing in α. Thus, for each value of τ, there is a cutoff $\hat{\alpha}$ such that for $\alpha > \hat{\alpha}$, negative assortative matching is stable and for $\alpha \leq \hat{\alpha}$, positive assortative matching is stable. Note tha $\hat{\alpha}$ may be greater than 1, in which case positive assortative matching is stable for all values of $\alpha \in [0,1]$. The continuity of $\hat{\alpha}$ follows from the continuity of f.

The cutoff $\hat{\alpha}$ is 1) increasing in τ when $\tau > \frac{\gamma}{w_{2f}}$ and 2) decreasing in τ when $\tau \leq \frac{\gamma}{w_{2f}}$ and the derivative f' is convex.

Totally differentiating and rearranging the surplus condition that determines the equilibrium matching gives

$$\frac{\partial \hat{\alpha}}{\partial \tau} = \frac{-w_{2f} f'(y_{HH}) - w_1 f'(y_{LL}) + w_1 f'(y_{HL}) - \frac{\partial y_{LH}}{\partial \tau} f'(y_{LH})}{f'(y_{HL}) \frac{\partial y_{LH}}{\partial \hat{\alpha}}}$$

It is sufficient to sign the numerator. When women Hi have no child, the first term of the numerator is 0 and $\frac{\partial \hat{\alpha}}{\partial \tau} > 0$. If f' is convex then $f'(y_{LH}) = m \cdot f'(y_{HH}) + (1-m) \cdot f'(y_{LL})$ and $f'(y_{HL}) = n \cdot f'(y_{HH}) + (1-n) \cdot f'(y_{LL})$. Substituting this in to the numerator gives $-w_{2f} f'(y_{HH}) - w_1 f'(y_{LL}) + w_1 f'(y_{HL}) - \frac{\partial y_{AL}}{\partial \tau} f'(y_{LH}) \leq [w_1 n + w_{2f} m - w_{2f}] f'(y_{HH}) + [-w_1 n + w_{2f}(1-m)] \cdot f'(y_{LL}) < 0$

y_{LH} is continuous but not differentiable at $\tau = \alpha$. However, it is easy to show that the subdifferential at $\tau = \alpha$ is the interval $[-w_{2f}, \frac{-w_1}{\alpha}]$ and the above derivative is negative for all values in this interval.

A.2.3 Proof of Theorem 2

The inequality that determines whether a man invests and enters occupation Hi can be written as

$$U_H - U_L + \eta_{Hm} - \eta_L \geq \eta_L + a_i$$

where U_H is the marital surplus received by a male Hi, U_L the marital surplus received by a male Lo, η_{Hm} is the outside option for a male Hi and η_L is the outside option for a (male or female) Lo. The left hand side of this inequality can be referred to as the "gains to entering occupation Hi" for a man. Note that the individual subscripts are no longer necessary because payoffs depend only on occupation.

The gains to entering occupation Hi can be re-written in terms of the total utility of couples. Without loss of generality, assume that positive assortative mating is the stable matching and men lawyers outnumber women lawyers. Then $U_H - U_L = Z_{HL} - Z_{LL}$ where Z is marital surplus and $\eta_{HL} - \eta_{LL} = Z_{HL} + \eta_{Hm} + \eta_L - Z_{LL} - \eta_L - \eta_L = U_H - U_L + \eta_{Hm} - \eta_L$ is the gains to becoming Hi and the cutoff ability type that invests in schooling is $a_i^* = \eta_{HL} - \eta_{LL} - \eta_L$. The same reasoning holds for other equlibrium marriage matchings and for women.

Women Hi never outnumber men Hi.

Assume for contradiction that they do. There are two possible stable outcomes:

1) Negative assortative matching. Then, recalling the assumption that the majority of individuals do not invest to beomce Hi, the total gains to Hi for a woman are given by $\eta_{LH} - \eta_{LL} - \eta_L$ and the gains to Hi for men by $\eta_{HL} - \eta_{LL} - \eta_L$. If women Hi outnumber men Hi, since the costs of schooling are symmetrically distributed by gender, the cutoff female ability type that invests

to become a Hi must be higher than that for men:

$$a_j^* > a_i^* \implies \eta_{LH} - \eta_{LL} - \eta_L > \eta_{HL} - \eta_{LL} - \eta_L$$

Because women Hi and men Lo are weakly less efficient in home production than women Lo, $\eta_{LH} - \eta_{HL} \leq 0$ and this cannot hold.

2) Positive assortative matching. If women Hi outnumber men Hi, the men Hi are the short side of the market. If the cutoff male ability that invests to become a Hi is $\eta_{HH} - \eta_{LH} - \eta_L$ and the cutoff female ability is $\eta_{LH} - \eta_{LL} - \eta_L$, it must be that $\eta_{LH} - \eta_{LL} - \eta_L > \eta_{HH} - \eta_{LH} - \eta_L$. For positive assortative mating to be stable, however, $\eta_{HH} - \eta_{HL} \geq \eta_{LH} - \eta_{LL}$. Putting these together implies that $\eta_{LH} > \eta_{HL}$ which is easy to show is false for all parameter values and thus women Hi cannot outnumber men Hi.

There are thus three possible equilibrium outcomes. There can be negative assortative mating where men Hi weakly outnumber women Hi, positive assortative mating where men Hi strictly outnumber women Hi, and positive assortative mating where there are an equal number of men and women Hi and the surplus from Hi-Hi couples is split so as to make the investment incentives identical for both genders.

The fraction of Hi who are women is 1) weakly decreasing in τ when positive assortative mating is stable, women Hi have a child, and f' is convex; 2) increasing in τ when positive assortative mating is stable and women in occupation Hi do not have kids; 3) increasing in α when negative assortative mating is stable.

Let a_j^* be the cost of schooling for the woman who is indifferent between schooling and not and a_i^* the cutoff for men. Then the fraction of Hi who are women is given by $FW = \frac{a_j^*}{a_i^* + a_j^*}$. Clearly in the region in which there are an equal number of men and women Hi, $FW = .5$. Thus one only needs to consider the regions in which men Hi outnumber women Hi.

The derivative of FW with respect to τ is $\frac{\partial FW}{\partial \tau} = \frac{\frac{\partial a_j^*}{\partial \tau} a_i^* - \frac{\partial a_i^*}{\partial \tau} a_j^*}{(a_i^* + a_j^*)^2}$ where the denominator is clearly positive. In all cases $a_i^* = \eta_{HL} - \eta_{LL} - \eta_L$ and $\frac{\partial a_i^*}{\partial \tau} = \frac{\partial}{\partial \tau}[\eta_{HL} - \eta_{LL} - \eta_L]$. There are three cases for the women. 1) Positive assortative mating is stable and women Hi don't have kids. Then $\frac{\partial a_j^*}{\partial \tau} > 0$ and $\frac{\partial FW}{\partial \tau} > 0$. 2) Negative assortative mating is stable. Then $\frac{\partial FW}{\partial \alpha} = \frac{\frac{\partial a_j^*}{\partial \alpha} a_i^* - \frac{\partial a_i^*}{\partial \alpha} a_j^*}{(a_i^* + a_j^*)^2} = \frac{\frac{\partial a_j^*}{\partial \alpha} a_i^*}{(a_i^* + a_j^*)^2} > 0$. 3) Positive assortative mating is stable and women Hi have kids. Let f' be convex. Then by the definition of convexity, there exists $m \in (0,1)$ such that $\frac{\partial a_i^*}{\partial \tau} \geq -w_1 m(f'(y_{HH}) - f'(y_{LL}))$ and $\frac{\partial a_j^*}{\partial \tau} \leq -w_1(1-m)(f'(y_{HH}) - f'(y_{LL}))$. Then $\frac{\partial a_j^*}{\partial \tau} a_i^* - \frac{\partial a_i^*}{\partial \tau} a_j^* < (\frac{\partial a_j^*}{\partial \tau} - \frac{\partial a_i^*}{\partial \tau}) \cdot a_i^* \leq (-w_1(f'(y_{HH}) - f'(y_{LL}))) \cdot a_i^* < 0$.

Thus, when f' is convex, the fraction of women FW increases from $\tau = \frac{\gamma}{w_{2f}}$ to the minimum of $\tau = 0$ or at the τ^* at which the model transitions to the 50/50 equilibrium where $\tau^*$is the solution to $\eta_{HL} - \eta_{LL} = \eta_{HH} - \eta_{HL}$.

A.2.4 Proof of Theorem 3

For a change in men Hi's wages, the static is straightforward from the convexity of f as $\frac{\partial \hat{\alpha}}{\partial w_{2m}} = \frac{f'(y_{HH}) - f'(y_{LH})}{f'(y_{LH})} / \frac{\partial p_{LH}}{\partial \hat{\alpha}} > 0$. For a change in w_{2f}, the effect on $\hat{\alpha}$ is given by $\frac{\partial \hat{\alpha}}{\partial w_{2f}} = \frac{f'(y_{HH}) \frac{\partial y_{HH}}{\partial w_{2f}} - f'(y_{LH}) \frac{\partial y_{LH}}{\partial w_{2f}}}{\frac{\partial p_{AL}}{\partial \hat{\alpha}}}$. If women Hi do not have a child then $\frac{\partial y_{HH}}{\partial w_{2f}} = 1$ and this is positive by the convexity of f. If $\frac{\partial y_{HH}}{\partial w_{2f}} = \frac{\partial y_{LH}}{\partial w_{2f}} = 1 - \tau$ this also positive. If $\frac{\partial y_{HH}}{\partial w_{2f}} = 1 - \tau$ and $\frac{\partial y_{LH}}{\partial w_{2f}} = 1$ then this is positive if $\frac{\partial \eta_{HH}}{w_{2f}} > \frac{\partial \eta_{LH}}{w_{2f}}$. Given τ and the convexity of f, this holds for sufficiently large w_{2m}.

Increasing w_{2f} increases the fraction of women since $\frac{\partial FW}{\partial w_{2f}} = a_i^* > 0$.

A.3 Proofs for Section 1.5

A.3.1 Proof of Theorem 4

The total utility generated by married couple man i and woman j can be rewritten as $\eta_{ij} = f(W_i + W_j + p_{ij})$ where W_i and W_j are the full income of individuals i and j and p_{ij} is the utility from a child minus the opportunity cost of their care. If a couple has no a child, $p_{ij} = 0$.

For ease of notation, I use indicator functions to represent piecewise solutions. 1_A is an indicator that is equal to 1 if the conditions for A are satisfied and 0 otherwise. Addition of indicators indicates "or" and multiplication indicates "and."

The net gain from children for Hi-Hi couples is given by

$$p_{HH} = \Big[\gamma - w_{2f}\tau - (1-\tau)\Delta(1_C\cdot(1-1_F)+1_D+1_E) - (\frac{w_{2m}}{\alpha} - w_{2f})(\tau - 1 + b)1_C\cdot 1_F\Big]\cdot 1_K$$

where C: $1-b < \tau \leq (1+\alpha)(1-b)$, D: $(1+\alpha)(1-b) < \tau \leq 1-b+\alpha$, E: $1-b+\alpha < \tau$, F: $\frac{(w_{2m}-w_{2f}\alpha)(1-b)+\alpha\Delta}{w_{2m}-\alpha w_{2f}+\alpha\Delta} \geq \tau$, and K: $\frac{\gamma-\Delta(1_C\cdot(1-1_F)+1_D+1_E)}{w_{2f}-\Delta(1_C(1-1_F)+1_D+1_E)} \geq \tau$.

If $\tau \leq 1-b$, women have a comparative advantage in home production and supply all of it. When $\tau > 1-b$, the couple must choose between sharing home production so that the woman can continue to work in the firm and having the woman switch to the spot market. Setting sharing equal to the woman working in the spot market gives the boundary for region F. Note that because I assume $b \geq \frac{w_{2f}+w_{2m}-\gamma}{w_{2f}+w_{2m}}$, the cutoff for not having children only binds when women Hi work in the spot market.

The net gain from a child for woman Hi - man Lo couples is given by

$$p_{LH} = [\gamma - w_{2f}\tau - (1-\tau)\Delta(1_E + (1_C+1_D)(1-1_A-1_B)(1-1_G)) - \Delta\alpha 1_E(1_A+1_B)$$

$$-(\frac{w_1}{\alpha} - w_{2f})[\min\{\tau,\alpha\}1_A + (\tau-(1-b))(1_C+1_D)((1-1_A-1_B)1_G+1_B)]]\cdot 1_{L1}\cdot 1_{L2}$$

where A: $\alpha > \frac{w_1}{w_{2f}}$, B: $\frac{w_1}{w_{2f}} \geq \alpha > \frac{w_1}{w_{2f}-\Delta}$, G: $\frac{(w_1-w_{2f}\alpha)(1-b)+\alpha\Delta}{w_1-\alpha w_{2f}+\alpha\Delta} \geq \tau$ and

$$L1: \frac{\gamma - \Delta(1_E+(1_C+1_D)(1-1_A-1_B)(1-1_G)) - \Delta\alpha 1_E(1_A+1_B) - (\frac{w_1}{\alpha}-w_{2f})\alpha 1_A}{w_{2f} - \Delta(1_E+(1_C+1_D)(1-1_A-1_B)(1-1_G))} \geq \tau$$

$$L2: \frac{\gamma + (\frac{w_1}{\alpha}-w_{2f})(1-b)(1_C+1_D)((1-1_A-1_B)1_G+1_B)}{w_{2f} + (\frac{w_1}{\alpha}-w_{2f})(1_C+1_D)((1-1_A-1_B)1_G+1_B)} \geq \tau$$

Note that when men Lo provide all child-related home production, the couple always has a child.

The husband still supplies home production when $\alpha > \frac{w_1}{w_{2f}}$ and the wife provides the residual if necessary. When $\alpha \leq \frac{w_1}{w_{2f}}$ and $\tau \leq 1-b$, the woman has a comparative advantage and provides all home production. When $\tau > 1-b+\alpha$, the woman provides all care if $\alpha \leq \frac{w_1}{w_{2f}-\Delta}$ and the man provides production α if $\alpha > \frac{w_1}{w_{2f}-\Delta}$. Thus, the only thing to solve for is whether the couple shares childcare or the woman Hi works in the spot market in the region $\tau \in (1-b, 1-b+\alpha]$

and $\alpha \leq \frac{w_1}{w_{2f}}$. Comparing opportunity costs, the couple prefers sharing to single person home production if $(1-\tau)\Delta > (\tau - 1 + b)(\frac{w_1}{\alpha} - w_{2f})$.

To compute the impact of increasing Δ on the region of shared labor supply in Hi-Hi couples, note that the two Hi share labor supply in the region $1_c \cdot 1_F$. Differentiating the cutoff for 1_F gives $\frac{(w_{2m}-w_{2f}\alpha)(1-b)+\alpha\Delta}{w_{2m}-\alpha w_{2f}+\alpha\Delta} = \frac{\alpha[w_{2m}-\alpha w_{2f}]b}{h^2} > 0$ so the area in which Hi share home production increases in Δ when the cutoff $(1+\alpha)(1-b)$ does not bind, i.e. for low α. A decrease in b increases the lower bound at which Hi-Hi couples share home production since both derivatives $1+\alpha$ or $\frac{(w_{2m}-w_{2f}\alpha)}{w_{2m}-\alpha w_{2f}+\alpha\Delta}$ are positive. Analogous reasoning holds for the men Lo - women Hi couples.

A.3.2 Proof of Theorem 5

From Lemma 1, there can only be negative assortative mating if men Lo provide some home production when married to women Hi. Thus, if women Hi always work in the spot market and men Lo do not have binding time budget constraints, positive assortative mating is stable. It is also easy to show that if couples with women Hi and men Lo have no kids then Hi-Hi couples also do not have kids since the opportunity cost of childcare is weakly smaller for couples with men Lo and women Hi.

Rearranging the equilibrium stability condition and implicitly differentiating with respect to Δ gives

$$\frac{\partial\hat{\alpha}}{\partial\Delta} = \frac{\frac{\partial p_{HH}}{\partial\Delta} f'_{HH} - \frac{\partial p_{LH}}{\partial\Delta} f'_{LH}}{\frac{\partial p_{LH}}{\partial\hat{\alpha}} f'_{LH} - \frac{\partial p_{HH}}{\partial\hat{\alpha}} f'_{HH}}$$

It is easy to see that the derivative is only non-zero in areas in which women Hi work in the spot market or on the boundaries between this region and others. If women Hi in Hi-Hi pairs work in the spot market and the men's time budget constraint does not bind, $\frac{\partial p_{HH}}{\partial\Delta} < 0$, $\frac{\partial p_{LH}}{\partial\Delta} = 0$, $\frac{\partial p_{HH}}{\partial\hat{\alpha}} = 0$ (because Hi type men only provide home production in the sharing region when both spouses are in the firm), and $\frac{\partial p_{LH}}{\partial\hat{\alpha}} > 0$. Thus $\frac{\partial\hat{\alpha}}{\partial\Delta} = \frac{\frac{\partial p_{HH}}{\partial\Delta} f_{HH} - \frac{\partial p_{LH}}{\partial\Delta} f'_{LH}}{\frac{\partial p_{LH}}{\partial\hat{\alpha}} f'_{LH} - \frac{\partial p_{HH}}{\partial\hat{\alpha}} f'_{HH}} < 0$. The functions p_{HH} and p_{LH} are continuous. At points at which they are not differentiable it is straightforward to check that $\frac{\partial\hat{\alpha}}{\partial\Delta}$ is negative for all values in the subdifferential of these two values since the sign of

$\frac{\partial\hat{\alpha}}{\partial\Delta}$ depends only on the sign of $\frac{\partial p_{HH}}{\partial\Delta}$ and $\frac{\partial p_{LH}}{\partial\hat{\alpha}}$.

The assumption that women and men Hi who share home production and both work in the firm always have kids ($1-b \leq \frac{\gamma}{w_{2f}+w_{2m}}$) implies that Hi-Hi couples always have a child when the woman can work in the firm. The cutoff $\hat{\tau}$ for which women Hi married to men Hi have no child and positive assortative mating is stable is thus defined by the equality

$$\gamma - \Delta = \hat{\tau}(w_{2f} - \Delta)$$

Totally differentiating gives $\frac{\hat{\tau}-1}{(w_{2f}-\Delta)} = \frac{\partial\hat{\tau}}{\partial\Delta} < 0$ which is negative since $\tau < 1$. The cutoff $\hat{\alpha}$ also increases as Δ increases when women Hi do not have children. Since women Hi - men Lo couples always have children when men Lo can provide all the childcare, and positive assortative mating is always stable when women Hi and men Lo have no children, the cutoff $\hat{\alpha}$must occur in the region in which men Lo spend all their time on childcare and women Hi complete the remainder. If women Hi can do this while still working in the firm, $\frac{\partial p_{LH}}{\partial\Delta} = 0$ and thus $\frac{\partial\hat{\alpha}}{\partial\Delta} = 0$. If women Hi must work in the spot market, then $\frac{\partial p_{LH}}{\partial\Delta} < 0$, $\frac{\partial p_{LH}}{\partial\hat{\alpha}} > 0$, and $\frac{\partial\hat{\alpha}}{\partial\Delta} > 0$. Since $\frac{\partial p_{HH}}{\partial\Delta} = 0$ and $\frac{\partial p_{HH}}{\partial\hat{\alpha}} = 0$, $\frac{\partial\hat{\alpha}}{\partial\Delta} > 0$.

A.3.3 Proof of Theorem 6

Recall that the fraction of Hi who are women can be written as $FW = \frac{a_j^*}{a_i^*+a_j^*}$. The proof of why men Hi outnumber women Hi from Theorem 2 still holds. Because cutoff for investment for men is always $a_i = \eta_{HL} - \eta_{LL} - \eta_L$, their gains to Hi do not depend either on Δ or b. Thus $\frac{\partial FW}{\partial\Delta} = \frac{(a_i^*+a_j^*)\frac{\partial}{\partial\Delta}a_j^* - \frac{\partial}{\partial\Delta}(a_i^*+a_j^*)a_j^*}{(a_i^*+a_j^*)^2} = \frac{a_i^*\frac{\partial a_j^*}{\partial\Delta}}{(a_i^*+a_j^*)^2}$. If positive assortative mating is stable, $\frac{\partial a_j^*}{\partial\Delta} = \frac{\partial[\eta_{HH}-\eta_{HL}-\eta_L]}{\partial\Delta} = \frac{\partial\eta_{HH}}{\partial\Delta} < 0$ if women Hi in Hi-Hi pairs work in the spot market and $\frac{\partial a_j^*}{\partial\Delta} = 0$ if they do not. If negative assortative mating is stable and the men's time budget constraint does not bind, women work in the firm and thus $\frac{\partial a_j^*}{\partial\Delta} = 0$.

A.3.4 Proof of Theorem 7

The returns to investment for women are either $\eta_{HH} - \eta_{HL} - \eta_L$ or $\eta_{LH} - \eta_{LL} - \eta_L$, while the returns to investment for men are not functions of Δ or b. Thus, a decrease in b increases the fraction of women when η_{HH} or η_{LH} is a function of b , which is when b is binding and women Hi share home production with men Lo.

A.4 Proof of Theorem 8

Since $\alpha' < 1$, men Hi never provide home production and thus are all equivalent in the marriage market. There are two cases: $\alpha \leq \hat{\alpha}$ or $\alpha > \hat{\alpha}$.

If $\alpha \leq \hat{\alpha}$, it is not profitable for women Hi to marry men with productivity α and all women Hi marry Lo with productivity α' or men Hi. Let V denote surplus to women and U surplus to men, and recall that Z is total marital surplus (total utility minus outside options). The increase in marital surplus from investing to become a Hi is given by $V_H - V_H = Z_{HH} - Z_{HL}$ (women), $U_H - U_L = Z_{HL} - Z_{LL}$(men with α) and $U_H - U_{L'} = Z_{HH} - Z_{L'H}$ (men with α'). The increased surplus given to men Lo with $\alpha_i = \alpha'$ is $U_{L'} - U_L = Z_{HL} - Z_{LL} - Z_{HH} + Z_{L'H} > 0$.

Because all male Hi get the same surplus, the additional surplus gained by men Lo with high α is lost gains to entering occupation Hi for these men. For this to be an equilibrium, the number of men Lo with α' must be less than the measure of women Hi. The condition for this is $q[a_{max} - (\eta_{LL} - \eta_{A'L} - \eta_A)] < \eta_{LL} - \eta_{LA} - \eta_A$. The left hand side holds for $q = 0$ and since it's continuous in q it must hold for q sufficiently close to 0. The returns to being a male Lo with high α are increasing in α' since $Z_{L'H}$ is increasing in α'.

An increase in women's wage w_{2f} decreases the returns to becoming a Hi for α' if $q[a_{max} - (\eta_{LL} - \eta_{A'L} - \eta_A)] > \eta_{LL} - \eta_{LA} - \eta_A$ or $\eta'_{AL} > \eta'_{LL}$. This is the same condition as in Theorem 3.

If $\alpha > \hat{\alpha}$ then all women Hi marry men Lo. The marital surplus gains to investing and becoming a Hi are $V_L - V_A = Z_{AL} - Z_{AA}$ (women), $U_L - U_A = Z_{LA} - Z_{AA}$ (men with low

α) and $U_L - U_{A'} = Z_{LA} - Z_{AA} - Z_{A'L} + Z_{AL}$ (men with α'). The condition on q for this to hold is

$$q[a_{max} - \eta_{LA} + \eta_{AA} + \eta_{A'L} - \eta_{AL} + \eta_A] \leq \eta_{AL} - \eta_{AA} - \eta_A$$

The derivative of the gains to high α men with respect to women's wages are $2w_1\tau(\frac{1}{\alpha} - \frac{1}{\alpha'})$. This is unambiguously positive, increasing in α', and decreasing in α.

If $\Delta > 0$ and τ, α, and α' are such that positive assortative mating and sharing is the stable matching, only men Hi perform home production. For q sufficiently small, men Hi with high α are outnumbered by women Hi and thus get to keep the additional surplus they create from their high efficiency. Since all men Lo receive the same surplus, men with high α have an additional incentive to invest in becoming a Hi.

Appendix B

Appendix to Chapter 2

The following notes apply to all tables and graphs.

- **Graduation year:** For individuals who took more or fewer than three years to finish law school, the graduation year is set to be their self-reported social class, which usually is three years after the year of matriculation.

  - **Cohort dummies**: dummies for graduation year in five-year groups (1970-1975, 1976-1980, etc.)

- **Undergraduate controls**: includes undergraduate GPA and dummies for undergraduate school.

  - **Undergraduate GPA:** normalized to have mean zero and unit variance within each graduating UMLS class.
  - **Undergraduate school**: includes dummies for Michigan alumni, other Michigan school, other state school, Ivy League / Seven Sisters, military, and foreign institutions.
  - **Ivy League / Seven Sisters**: Attended college at an Ivy League or Seven Sisters school.

- **First job**: First job after graduation, or after serving as a clerk if clerkship is first job. Categories include law firm, corporate counsel, government / public service, and other.
- **Law school performance**:
  - **Law school GPA**: Normalized to have mean zero and unit variance within each graduating class.
  - **LSAT percentile**: Percentile of the individual's LSAT score among all test-takers nationally the year prior to matriculating at UMLS.
  - **Transfer student**: entered UMLS after the first year. Undergraduate and LSAT information may be missing for transfer students.
- **Labor supply**:
  - **Not employed**: reports currently working zero hours per week or zero weeks per year.
  - **Part-time**: reports working 35 or fewer hours per week, one or more weeks per year.
  - **Ever part-time**: reports working part-time for six or more months between law school and the survey.
  - **Ever not employed**: reports being out of the labor force for six or more months between law school and the survey.
- **Workplace setting**: includes dummies for law firm, corporate counsel, government / public interest / legal services, and non-practice setting.
- **Non-practice setting**: includes dummies for judiciary, teaching, business, non-profit, and other.
- **Marital status:**
  - **Ever married**: Currently married, divorced, separated, or widowed.

  - **Married**: Currently married or re-married. Includes cohabiting relationships in which partner occupation and income are reported.

- **Race controls**: include dummies for African American, Hispanic, Asian, White, and Other.

- **Location controls**: dummies for current census region and population of current city of work.

Appendix C

Appendix to Chapter 3

C.1 Assumptions on the Peer Effects Production Function

Here we discuss the assumptions underlying the peer effects specification in Section 2. Much of this notation and many of the assumptions in this section are taken from Graham et al. (2010).

Consider a population of individuals ("students") assigned to groups ("classrooms") of N individuals each. Each student is indexed by i and each classroom is indexed by c. Let the variable C_i indicate the group assignment of individual i: $C_i = c$ indicates that student i is assigned to classroom c. For brevity, denote by c_i the class of student i. Student i had a pre-assignment vector of observed characteristics X_i and unobserved characteristics A_i. Denote by $Z_i = (X_i, A_i)$ the vector of all characteristics for individual i. Each class has group-specific characteristics G_c, such as classroom facilities and teachers. We observe the student's performance after being in class c; we denote this outcome Y_i. Y is generated by the production function

$$Y = \tilde{f}(Z, \boldsymbol{Z}, \boldsymbol{C}, \boldsymbol{G}) + \epsilon$$

where $\boldsymbol{Z}$ is the vector of characteristics Z for all individuals in the population, $\boldsymbol{C}$ is the vector of group assignments in the population, $\boldsymbol{G}$ is the vector of characteristics of all groups, $E(\epsilon) = 0$,

$Var(\epsilon) = \sigma^2$, and ϵ is independent of $\mathbf{Z}, \mathbf{C}$, and $\mathbf{G}$.

Student $i's$ outcome is independent of the characteristics Z_j of students j not in $i's$ class, of the assignment of individuals not in $i's$ class to classes, and of the characteristics of classes to which i is not assigned. More formally,

$$\tilde{f}(Z_i, \boldsymbol{Z}, \boldsymbol{C}, \boldsymbol{G}) = \hat{f}(Z_i, Z_{-i}, G_{c_i})$$

where $Z_{-i} = \{Z_j | C_j = c_i, j \neq i\}$.

This assumption eliminates general equilibrium-type effects such as a population-wide grading curve in which the composition and resources of the overall population affects student i's outcome.

We next assume that only the characteristics, not the labels, of student i's classmates affect her outcome.

The production function is *exchangeable* in Z_j, $j \neq i$. That is, for any permutation $\tilde{Z}_{-i}$ of Z_{-i},

$$\hat{f}(Z_i, Z_{-i}, G_{c_i}) = \hat{f}(Z_i, \tilde{Z}_{-i}, G_{c_i})$$

Under this assumption of exchangeability,we can re-write the production function as

$$E(Y_i | Z_i, Z_{-i}, G_{c_i}) = \vec{f}(Z_i, F_{Z_{-i}}, G_{c_i})$$

where $F_{Z_{-i}}$ is the empirical distribution of Z_j for the $N-1$ classmates of student i. Manski (2011) refers to social interactions of this form as *distributional interactions*.

$X_i \perp A_i$

This is a mechanical assumption: for any individual unobservables A_i^*, we can define $A_i = A_i^* - E(A_i^* | X_i)$.

Students are randomly assigned to peer groups, and groups are randomly assigned to facilities (including teachers), conditional on a subset $\tilde{X}_i$ of the variables X_i.

$$Z_j \perp Z_i | \tilde{X}_i \ \forall j \text{ s.t. } C_j = c_i, j \neq i$$
$$Z_k \perp G_c | \tilde{X}_i \ \forall k \text{ s.t. } C_k = c$$

Examples of variables $\tilde{X}_i$ could include demographic variables used for stratified random assignment (for example in Carrell et al. (2009)) or school-level dummies. This is a generalization of double randomization as first introduced by Graham (2008).

Finally, we make an assumption about the sampling used which allows for straightforward bootstrapping.

We observe a sample of M classrooms randomly drawn from the population of classrooms.

Thus, the observed data consists of vectors (Y_i, X_i, C_i) for all i in the M classrooms randomly sampled.

C.2 Local Linear Regression

The local linear regression estimates in Figures 3 through 6 are computed using a multidimensional Epanechnikov kernel. The bandwidth is the rule of thumb bandwidth for local linear regression of Fan and Gijbels (1996) given by

$$\hat{h}_{ROT} = 1.719 \left[\frac{\breve{\sigma}^2 \int w_0(x) dx}{\sum_{i=1}^{n} \{\breve{m}^2(X_i)\}^2 w_0(X_i)} \right]^{\frac{1}{5}}$$

where n is the number of data points in the sample, $\breve{m}(x)$ is the estimate of $m(x) = E(Y|X = x)$ using a quartic polynomial, $\breve{m}^2(x)$ is the second derivative of $\breve{m}(x)$, $\breve{\sigma}^2$ is the sum of squared residuals from the estimate of $\breve{m}(x)$, and $w_0(x)$ is the indicator function over the domain of $m(x)$. For more detail, see Chapters 3 and 4 of Fan and Gijbels (1996).